



Energy-efficient control of shopping center HVAC

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ENERGY-EFFICIENT CONTROL OF SHOPPING CENTER HVAC

**BY
JOAKIM BØRLUM PETERSEN**

DISSERTATION SUBMITTED 2020



AALBORG UNIVERSITY
DENMARK

Energy-efficient control of shopping center HVAC

Ph.D. Dissertation
Joakim Børlum Petersen

Dissertation submitted December, 2020

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Abstract

Building control, which covers the control of the Heating, Ventilation and Air Conditioning (HVAC) installations in a building, is an important research area to reach climate targets. The potential for energy savings within buildings is immense and the ability to unlock it using control is cost-effective. Furthermore, building control can enable and expose the inherent energy flexibility and support the further penetration of renewable energy generation in the grid. Model Predictive Control, which has been the pinnacle within process control, is widely treated in the building control literature and it has been proven capable of both reducing energy consumption and introducing energy flexibility. However, with the majority of the building stock being old, building control has to be considered in the context of retrofitting. As research has shown, Model Predictive Control may not be well-suited in this context – which may also be indicated by the industry not adopting the method.

This thesis is concerned with alternative tractable control methods and feasible implementations of building control. These topics are treated in the context of shopping centers, which poses further constraints on tractability due to their complex HVAC systems. The research has been carried out under the Smart Energy Shopping Centers EUDP project. The main contributions is the formalization of a general low-complexity hierarchical control methodology to complex HVAC systems and the inclusion of Iterative Learning Control, to provide both energy savings and maintained thermal comfort. The methodology intentionally focuses on information available by interfacing directly with existing Building Management Systems to maximize the retrofit compatibility.

The proposed method is applied to two Danish shopping centers exhibiting different consumption characteristics and with different HVAC architectures. The two case studies have been thoroughly analyzed in terms of how it is possible to interface with them through the existing Building Management System infrastructure and a piggybacking-method was proposed and evaluated through different control experiments – this is concluded a highly feasible way of introducing new building control in the existing building

stock.

Simulation studies show promising results in both cases, with energy savings in the range 10-22%. In a comparison with Model Predictive Control, the proposed method is very close to providing the same performance in terms of both energy savings and maintaining thermal comfort – with significantly less complexity and modeling overhead. Furthermore, a control experiment over 3 months in one of the case studies showed energy savings as high as 30-40%.

Resumé

Bygningskontrol, som dækker styring af varme, ventilation og aircondition (HVAC) i en bygning, er et vigtigt forskningsområde for at nå klimamål. Der er et umådeligt stort potentiale for energibesparelser indenfor bygninger, og muligheden for at indfri det igennem bygningskontrol er omkostningseffektivt. Ydermere kan bygningskontrol aktivere og eksponere energifleksibilitet for videre at understøtte en højere grad af vedvarende energi i forsyningen. Model Prædiktiv Kontrol (MPC), som har været højdepunktet indenfor proces kontrol, er i et stort omfang også behandlet i bygningskontrol litteraturen og har vist sig egnet til både at reducere energiforbruget og til at introducere energifleksibilitet. Eftersom hovedparten af den eksisterende bygningsmasse er gammel skal ny bygningskontrol tænkes ind i en eftermonterings-kontekst. Forskning har vist, at MPC ikke nødvendigvis er velegnet i denne kontekst – hvilket muligvis også kan ses i den manglende anvendelse af MPC i bygningskontrol industrien.

Denne afhandling undersøger alternative medgørlige metoder og gennemførlige implementeringer af bygningskontrol. Disse emner er behandlet indenfor shopping centre, som sætter yderlige begrænsninger til metoderne grundet shopping centres komplekse HVAC systemer. Forskningen er tilblevet under Smart Energy Butikcentre EUDP projektet. Hovedbidraget er en formalisering af en generel og simpel hierarkisk og iterativ lærings kontrol (ILC) metode til at varetage kontrol af komplekse HVAC systemer, for både at sænke energiforbruget og bibeholde termisk komfort. Metoden fokuserer bevidst på information der allerede er tilgængeligt ved at interface direkte med eksisterende bygningsautomatik (CTS) for at maksimere kompatibiliteten i en eftermonterings-situation.

Den foreslåede metode er anvendt på to danske shopping centre med meget forskellig køle- og varmekonsum og med forskellige HVAC systemer. De to casestudier er blevet analyseret i forhold til hvordan det er muligt at interface med deres eksisterende bygningsautomatik og en 'piggyback'-metode blev foreslået og evalueret gennem forskellige kontrol eksperimenter. Der konkluderes at denne tilgang bestemt er en mulighed når der skal introduces ny bygningskontrol i den eksisterende bygningsmasse.

Simuleringsstudier har vist meget lovende resultater i begge casestudier, med energibesparelser mellem 10% og 22%. I en sammenligning med MPC viser den foreslåede metode at denne kan opnå næsten de samme resultater når der er tale om energibesparelser uden at gå på kompromis med termisk komfort – og dette med signifikant lavere kompleksitet og uden at være afhængig af en tidskrævende dynamisk model. Ydermere har et kontrol eksperiment kørt over 3 måneder i et af de to shopping centre vist energibesparelser mellem 30% og 40%.

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Contents

Preface

This thesis is submitted as a collection of papers in partial fulfillment of the requirements for the degree of Doctor of Philosophy at the *Section of Automation and Control, Department of Electronic Systems, Aalborg University, Denmark*. The work covered by this thesis has been carried out in the period from September 2017 to November 2020.

I would like to thank my supervisors, Professor Jakob Stoustrup and Associate Professor Jan Dimon Bendtsen for their invaluable support and guidance. While not officially noted as a supervisor, Professor Andrew G. Alleyne deserves an enormous amount of credit. I had the opportunity to visit Professor Alleyne and the Alleyne Research Group at the University of Illinois at Urbana-Champaign in February 2019. After this visit, Professor Alleyne has been an integral part in my research. Sadly, a global pandemic prevented a second planned visit.

I would also like to extend thanks to the project partners in the SEBUT project, under which the research in this thesis has been carried out. It was especially the SEBUT project which enabled the access and possibility of conducting experimental work at the two Danish shopping centers; Kolding Storcenter and CITY2. For this possibility, a special thanks is extended to the project partners, Ulrik Sloth Christensen at DEAS and Christian Christiansen at the Danish Technological Institute (Teknologisk Institut). For their invaluable support and fruitful discussions a special thanks is also extended to the project partners from Neogrid Technologies ApS.

Juan de Dios Flores Mendez, while not actively contributing to the research, deserves maybe the biggest mention. He and I shared an office during the majority of the work and these times will be sorely missed. Together with Shibarchi Majumder, Glenn Andreasen, Jorge Val Ledesma, Krisztian Mark Balla and the entire staff of Automation and Control they made the experience worthwhile.

Joakim Børllum Petersen
Aalborg University, December 19, 2020

Preface

Part I

Summary

1 | Introduction

1.1 Buildings and their energy consumption

With the current pace and extent of the global energy transition, climate targets can not be met. Energy-related CO₂ emissions need to peak in 2020 and then enter a very steep descent to succeed in reaching goals – in 2018 emissions went up by 1.7 % and in 2017 they went up by 1.6 % [1].

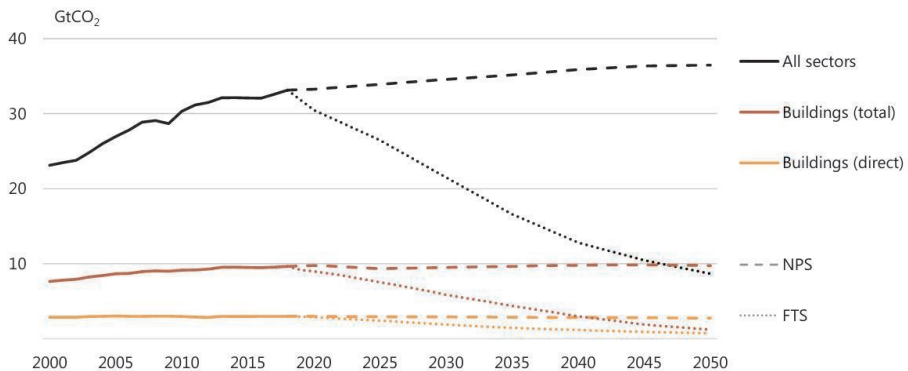


Fig. 1.1: Energy-related CO₂ emissions in Gt for all sectors and for buildings. Direct consumption is without emissions from consumption of electricity and e.g. district heating. The New Policies Scenario (NPS) is the expectation given the current policies, measures and announcements. The Faster Transition Scenario (FTS) is an ambitious scenario aligned with the long-term goals of the Paris Agreement [1].

Buildings are, globally, responsible for approximately one third of the total energy consumption. This has buildings playing a critical role in reducing emissions. While measures are being taken, and the consumption per square meter has been reduced, it has not been able to keep up with the massive increase in floor area, leaving energy-related CO₂ emissions from buildings 25 % higher than in 2000 [1].

When it comes to increasing energy efficiency of buildings, this is either done by increasing the efficiency of the building envelope or the efficiency of

the Heating Ventilation and Air Conditioning (HVAC) equipment. Denmark and Germany have been progressive within making energy efficiency policies for the building envelope – where e.g. Korea and Japan are focusing more on HVAC equipment. In order to meet climate targets, both areas are highly critical, as very efficient envelopes also enable the use of even higher-efficiency (e.g. low temperature) HVAC equipment[2].

As the majority of the existing building stock is old, an important consideration is retrofitting. Updating the building envelope can in a retrofit situation be very expensive, making investments in energy refurbishment unattractive. With HVAC equipment responsible for 50 % of energy spent in buildings[3], it can be more attractive to update old installations. One way is by replacing old equipment with new more efficient equipment. Another way is to consider that a majority of the energy consumption is due to how the equipment is operated, making it a *control* problem.

Another aspect of buildings and their large energy consumption, is the role they are going to play in a progressively different energy system. To combat the energy-related CO₂ emissions, renewable energy is penetrating the electricity supply. In 2019, renewables accounted for 26 % of global electricity generation and have been growing steadily since 2000, where it was 18 %[4]. The penetration of renewable energy entails an increasingly stochastic electricity generation, which poses new requirements to balancing the production and consumption. One way to balance production and consumption is to have the consumers actively participate, providing *demand response*; e.g. load-shifting, peak-shaving or ramping. This is possible in buildings by allowing temperatures to vary within a comfort band, exploiting the thermal capacity. Unlocking this energy flexibility in buildings is also a *control* problem.

These two control problems are the topics of this thesis.

1.2 Building control – state-of-the-art

In single family housing, HVAC control is often reduced to the control of a single heating or cooling solution, depending on the climate. The control problem is then boiled down to operating a single piece of equipment as efficiently as possible. In larger buildings – both commercial and residential – the complexity of the HVAC setup increases with the scale of the building. To manage this complexity (together with a myriad of other building installations), a Building Management System (BMS) or Building Automation System (BAS) is employed.

The BMS is the over-arching control system of a building, connecting all relevant installations (HVAC, lighting, windows, etc.) and providing a building operator with a single interface to supervise, schedule and operate these

1.2. Building control – state-of-the-art

installations. A conceptual drawing is presented in **Figure 1.2a**. The building operator is tasked with setting schedules, setpoints, operating modes and supervising the operation of the underlying installations. With the recent availability of both data storage, processing power and cheaper sensors, BMS suppliers have been pushed to deliver on e.g. predictive maintenance and predictive control. This is however not the standard to be expected. Looking at **Figure 1.2a**, it is natural to look at building control from a hierarchical control point-of-view. This is depicted in **Figure 1.2b**.

The existing building stock is mainly controlled by means of decentralized PID controllers (*Automation level* in **Figure 1.2a**, *Local controllers* in **Figure 1.2b**) for temperature control[5, 6]. Supervisory control is mostly in the form of scheduling ON/OFF, night-setback[5] and setpoint curves for ambient temperature compensation[7].

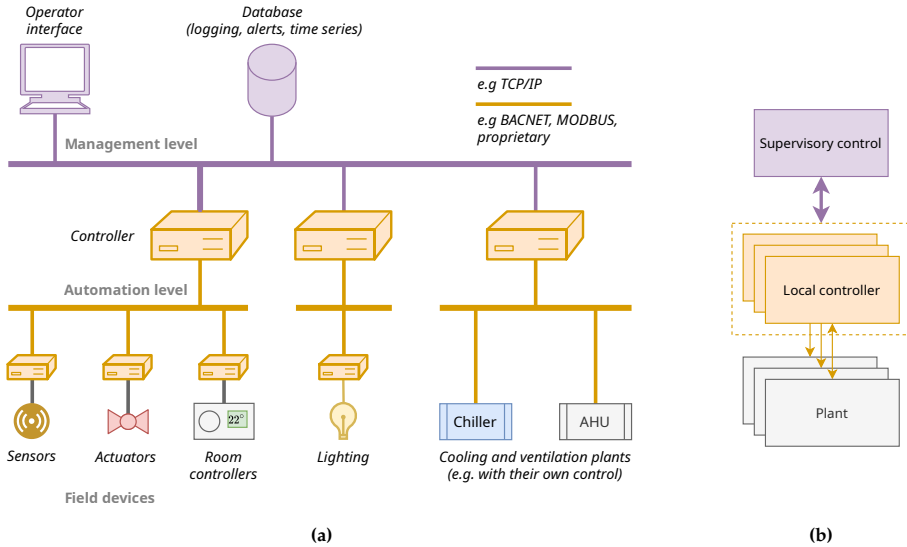


Fig. 1.2: (a) BMS (or BAS); the overarching control solution in larger buildings.
(b) Inferred hierarchical control perspective on BMS.

The main drawback of relying on PID control in building automation is due to changing non-linear building dynamics. With PID controllers commissioned with constant parameters, their performance will degrade if they are not re-tuned. This can lead to instabilities, under- and overshoots, at the cost of both thermal comfort and energy consumption. This has been known since the 1980s with a significant amount on research within adaptive, predictive and optimal control as a reaction[8]. But even with several decades of research in building control, there has been very little industry adoption.

1.2.1 Model Predictive Control

Over the last decade, the majority of building control literature has been focused on Model Predictive Control (MPC) as reported in both [8] and [9]. There are several reasons why research into the application of MPC is attractive. Using MPC in a building control application naturally allows for:

- posing a cost to be minimized; e.g. thermal comfort and or energy consumption
- including predictions of ambient conditions, occupancy, electricity prices, etc.
- enforcing constraints on e.g. room air temperatures and actuator limits
- guaranteeing stability and robustness[10]
- enabling demand response applications

On top of this, MPC is a success story in process control and the drawbacks in terms of computational complexity have with both research into computational efficiency and the growing availability of processing power been significantly diminished[11].

In the works treated in both [8] and [12] the results of using MPC are very promising in terms of reductions in energy consumption. The most convincing results are experimental studies, showing the results from an actual implementation of MPC.

Energy savings of 15 % to 28 % were reported in [13], where the authors applied MPC in the buildings of the Czech Technical University, from January 2010 to March 2010. The MPC was compared to the performance of the heating curve otherwise used.

In [14] the authors present a multi-objective MPC, optimizing both energy consumption, operating cost and occupancy comfort – with online occupancy feedback. The controller was demonstrated in two office buildings in Australia, in a trial during two winter months. Comparing with the performance of using the existing BMS, energy savings were reported as 19 % and 32 %, and with no degradation of comfort.

In [15] the authors present an MPC design, minimizing energy consumption and thermal discomfort. From an implementation and trial in an office building in Belgium, the authors report energy savings of 30 % during winter, while providing similar or better thermal comfort. Another office building in Belgium has been the case study in the work presented in [16]. Here a cloud-based MPC solution is presented and results from five months of operation are reported. Savings were reported as high as 53 % and with significant improvements of thermal comfort.

A larger academic building (10 000 m²) in Canada is treated in [17], where MPC is implemented and tested during four months. The results showed reducing HVAC energy consumption by 30 %. The authors conclude that this exceeds expectations, given that several measures had already been taken to improve energy efficiency in the building.

In [18] a seven month long MPC experiment in a Swiss office-building was conducted. While the results in terms of energy savings are indeed promising, the authors conclude through a cost-benefit analysis that initial costs may simply be too large to justify the use of MPC. One very significant cost being the modeling tasks involved, given the time effort. The authors of [18] conclude that this is especially the case for older buildings with very sparse information on the building available. This is a major issue for the application of MPC, as the largest potential for energy savings through control is in older buildings. In [19], [20] and [21] the authors also regard the modeling effort as the largest cost to unlock the benefits.

Many works treat the different approaches to modeling building dynamics, as there is no silver bullet[19]. When the goal is a control-oriented model, there are three main modeling paradigms:

- White-box models
- Grey-box models
- Black-box models

The distinction between these is in how much one relies on first-principles and how much one relies on statistics. A white-box model is a purely physics-based first-principle analytical model. A black-box model is a purely statistics- or data-driven model. The grey-box model is the hybrid of the two. Often the grey-box models are Resistor Capacitor (RC)-equivalent models which lends themselves well to large multi-zone buildings[20]. Looking at the experimental MPC studies cited above (all of them considering larger multi-zone buildings), they all use grey-box models – except for [16], where the authors use a white-box model. The compromise of using a grey-box approach lends itself well to a retrofit situation; maybe not enough data is available to pursue a purely data-driven approach, while at the same time, not enough information about the construction is known to construct a white-box model.

In the case that there is an abundance of data available, data-driven methods (black-box) can be very attractive, especially in a retrofit situation, with limited information on the building[22]. But quantity of the data is not enough; the measurements used in the identification of a black-box model has to cover input-output data in all operating conditions. There have been experimental studies of using black-box models[23, 24], but not as elaborate and complete as in the previously mentioned grey-box and white-box cases.

1.2.2 Tractable methods

The authors of [19] conclude that the main barriers to MPC adoption are:

- Added engineering effort
- Required engineering qualifications
- Risk mitigation
- Industry reluctant to adopt

Together with the barriers of interfacing with legacy automation systems and a lacking instrumentation level, this severely hinders the widespread adoption of more advanced control methods – especially considering retrofit applications[25]. With these boundary conditions, there is room for alternative building control methods, with a focus on being *tractable*.

In [26] the authors focus on low-complexity methods to improve implementability. The work investigates using different steady-state setpoint optimization schemes to lower energy consumption in different HVAC case studies. The authors conclude that simple methods are sufficient drastically reduce energy consumption. In [27] another alternative control strategy is proposed, which is a model-based design that has gone through several simplification steps.

The authors of [28] also respond to the slow adoption of MPC, and propose a method to learn a Rule-Based Control (RBC) scheme from simulations with MPC. In a comparison study it was shown that the learned RBC performed adequately well in six different case studies with different buildings – without having to relearn the controller for each building. While the method still relies on learning from an initial MPC, the prospect of moving the learned control to different buildings is very attractive. To some extent, the same approach is taken in [29]. Here the author produces look-up tables of MPC response, by pre-computing the results for a grid of disturbances. This is a computationally intense task, but this effort only has to be done once before implementation – the author does however conclude that dimensionality is an issue which limits application of this approach.

In [30] the authors investigate MPC to the effects of several uncertainties (measurement errors, occupancy and model-mismatch) on energy consumption and occupancy comfort. The authors conclude that implementation costs can be reduced by not including prediction of ambient temperature and thermal load – and this without compromising the controller performance. In [31] the authors compare a simple feedback controller using occupancy information to MPC. Results show that the feedback controller performs almost as good as MPC.

These alternative methods, while easier to implement and commission, are still lacking compared to all the features of MPC; prediction being one of

them. Given a forecast of a disturbance, e.g. ambient temperature, predictive capabilities can be included using feed-forward control, which is relatively simple. Furthermore, buildings are often subjected to disturbances that exhibit repetitive patterns; both outside weather, occupancy and HVAC operation. Using past recorded information to iteratively update the feed-forward control is called Iterative Learning Control (ILC). Historically, ILC was introduced for manufacturing and robotics applications where the same task is repeated over and over again[32]. The method has however also appeared in the building control literature. In [33] ILC (or Repetitive Control) is used to improve temperature regulation in a simulation of an office building. The authors show a tracking performance improvement of 50 % without any increase in energy consumption. In [34] and [35] the authors also present the use of ILC for temperature regulation; but instead of a classical ILC approach looking one iteration/trial back, the authors propose methods to find a day in historical data that best matches the upcoming day – and use this in the application of feed-forward. In [36] the authors propose a combination of MPC and a database-driven ILC, showing through simulations that the addition of ILC improved the performance over using only MPC. The authors conclude that it is a promising combination. In [37, 38, 38] the authors investigate optimization-based ILC for large-scale building temperature regulation, determining optimal learning gains by solving a convex optimization problem which takes into account, among others, thermal comfort constraints and input saturation constraints. The topic of large-scale buildings is also treated together with ILC in [39], where the authors propose decentralized ILC for building temperature control showing performance benefits when compared to a distributed consensus approach. Such a distributed approach is considered in [40].

While ILC has been investigated in terms of building control, the area is by no means well-explored and the results reported in the literature show that it is a promising approach to exploit the inherent repetitive behavior in buildings.

1.2.3 Energy flexibility

Energy flexibility (or demand response) within the domain of building control has been studied extensively, and the classification of different energy flexibility measures has been discussed in several works[41, 42]. In general, there are two major categories within energy flexible control; *indirect control* and *direct control*.

Indirect control considers price-signals, and lets the consumer (building) decide how to act on this. This can be electricity pricing 24 h ahead as available in the NordPool day-ahead market or it can be peak-tariffs/critical peak pricing. By having the building adjust their consumption to low-price hours,

the building has a possibility to save on their electricity bill – and as low-price hours on the day-ahead market are correlated with excess production, this will help to balance the grid.

Indirect control through a price-signal can be achieved using methods of lower-complexity (e.g. RBC), as indicated in [43] and demonstrated in [44]. However, to exploit storage possibilities due to thermal mass in buildings, MPC is an obvious choice as also indicated by the literature[45].

For direct control, the consumer (building) has to meet a specified consumption profile in a given time-slot[46]. This requires the utility company requesting the power curtailment, to have a certain level of control over equipment in the building. Direct control allows for deterministic load-shifting and peak-shaving services. Direct control for commercial building HVAC is demonstrated in [47] using a method that does not depend on modeling the building dynamics, showing over 15 % peak-demand reduction in a building with four roof-top Air Handling Units (AHUs).

Direct control is especially interesting, as it can allow for ramping, which has been identified as an important demand response service to alleviate standby coal, oil and gas fuelled electricity production in grid systems with high Photovoltaic (PV) penetration[48]. The problem is coined the "duck curve" problem[49] due to the shape of the net load curve (**Figure 1.3**); the difference between total actual electricity load and production by renewable energy. In [50] the authors investigate the ramping rate of HVAC loads and conclude that aggregated HVAC units can provide a fast regulating reserve service to support in alleviating the "duck curve" problem.

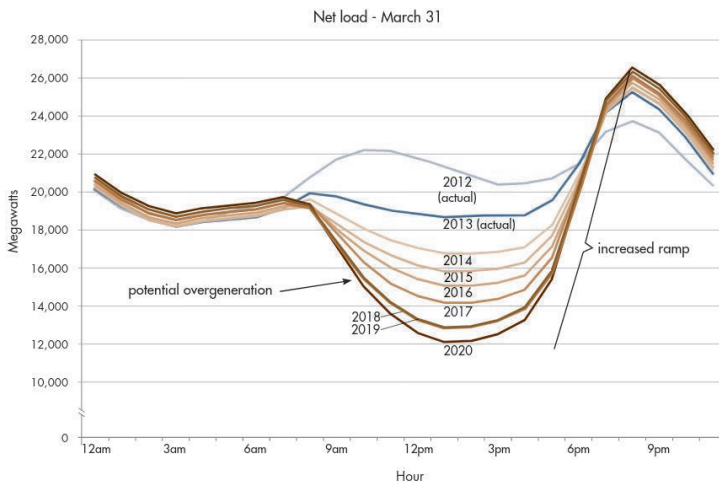


Fig. 1.3: The now famous "duck curve" of CAISO; California Independent System Operator. Showing net load: the difference between actual total electricity load and renewable energy generation.[49]

1.3. Smart Energy Shopping Centers

The above sections have introduced the energy efficiency and energy flexibility control problems and the associated state-of-the-art within building control. In this thesis the topic has been a specific class of buildings, namely shopping centers.

1.3 Smart Energy Shopping Centers

The work in this thesis has been carried out under the Danish joint research project, Smart Energy Shopping Centers (SEBUT)¹. As shopping centers (or shopping malls, see **Figure 1.6**) use 25 % to 30 % of the total energy consumption of the Danish retail sector, the impact of improving energy efficiency and potentially introducing energy flexibility is large. The goal of the project is to develop intelligent building control, knowledge services, guidelines and tools for energy refurbishments of shopping centers in Denmark. The involved project partners (**Figure 1.4**) are:



Fig. 1.4: Project partners in the joint research project SEBUT.

Danish Technological Institute Private research institute (**project manager**)

Neogrid Technologies Intelligent building control and services

DEAS Building administrator

Bitzer Supplier of ventilation and cooling controls

Exhausto AHU manufacturer

A Comfort Cooling supplier

New Nordic Engineering Indoor air quality sensors

Aalborg University Automation and Control section

¹Smart Energy Butiksentre

The project work is divided into the Work Packages (WP) presented in **Figure 1.5**, highlighting the parts (green) that were central to the work in this thesis: WP 2 and 3 deal with defining control problems and models. WP 5 is on the practicalities of making demonstrations a possibility, while demonstrations are carried out in WP 6.

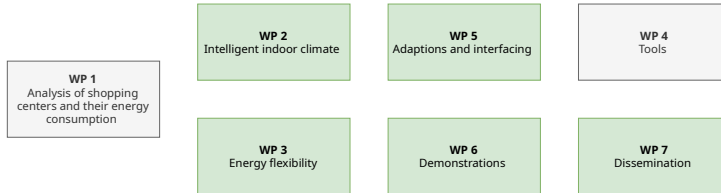


Fig. 1.5: Work packages in SEBUT, highlighting the ones directly involved in the work of this thesis (green).

From a research point of view, building control within a shopping center context has only received limited attention in the literature. But as a large commercial building, there is plenty of previous work to draw on, as presented in **Section 1.2**. Shopping centers do, however, possess some salient characteristics.



Fig. 1.6: Kolding Storcenter entrance. A Danish shopping center treated in the SEBUT project.

There can be some confusion on the term *shopping centers*. In the SEBUT project, a shopping center is a large commercial building, complete with common area and shops. On average, 40% common area to 60% shops. The shops are mainly retail shop, but there will often also be supermarkets and restaurants – and in larger shopping centers perhaps a cinema. Shops are leased to holders by the shopping center administrators. The lease holders are responsible for the interior of the shops, this also includes lighting. The

lease holders are billed for their own consumption of electricity.

An acceptable indoor climate is ensured by the operation of HVAC, supplying e.g. ventilated air to the shops, that is either cooled or heated. This is the responsibility of the shopping center administrators – or more specifically the building operators. The HVAC expenses will often be divided among the lease holders by the size of their shop.

There are some key characteristics that make shopping centers stand out from being classified as generic commercial buildings. First of all, as shops are leases, the lease can change holder with a relatively high frequency; shops close down and new shops open up. When this happens, the interior of the shops change, complete with appliances and specifically *lighting*. This means that heating and/or cooling demand for shops can change drastically. It may also happen, that larger shop areas are divided into smaller separate shops – or the other way around. These changes to the floor plan has a significant impact on the control, as zones have to be redefined.

Generally, retail shops feature excessive display lighting to showcase what they are selling. In the cases where lighting has not been fully, or at all, converted to LED, this generates a significant amount of heat. This added heat gain means that shopping centers often feature large cooling demands – even in colder climate[51].

1.4 Research objectives

As emphasized in **Section 1.1**, buildings have a responsibility in changing their energy consumption to reach desired global climate targets. This change has to be both in terms of energy efficiency and energy flexibility. The building control literature has already shown methods and experiments that demonstrate the benefits. The industry has still not adopted these methods, however. Hence, the goal of this Ph.D. study is to investigate the potential of alternative tractable methods. As the Ph.D. study is carried out under the SEBUT project, this will be in the context of shopping centers. The following objectives have been defined:



Investigate feasibility of interfacing with existing building control

The majority of the existing building stock is old. To facilitate new control, a method to interface with existing building control is needed. This is a significant part of the demonstration effort in the SEBUT project and will be investigated in the setting of shopping centers, which feature large and complex building control setups.



Formulate a model for both simulation and control purposes

A simulation model will allow fast evaluation of new control algorithms, and for reproducing results under different ambient conditions. Besides simulations, a model is an integral part in any model-based control design.



Investigate the use of Model Predictive Control

MPC is the state-of-the-art within building control and is also the most noteworthy control methodology when it comes to providing energy flexibility. In order to propose alternative methods it was found necessary to first attempt the most complex approach with the most promising results to establish a performance bound.



Propose an alternative method to introduce energy efficiency

Based on experience and results of using MPC this Ph.D. study will attempt to formulate a general control methodology, applicable to shopping centers in general. This control methodology should stand as an alternative to MPC in order to provide a practitioner with options, when it comes to a building control retrofit situation.



Investigate potential for energy flexibility in shopping centers

To accommodate flexible electricity production, electricity consumers need to be flexible as well. This Ph.D. study will investigate the potential for energy flexibility in shopping centers.

1.5 Preview and contributions

This section presents the contributions to the state-of-the-art in the form of the associated papers. For each paper, a brief introduction is given together with a highlight of the specific contributions. The papers are presented in full in **Part II**.

Paper A

J. B. Petersen, J. Dimon Bendtsen, and J. Stoustrup, “*Multi-Zone Modeling and Energy Efficient Control of Shopping Center Cooling*,” in 2018 IEEE Conference on Control Technology and Applications (CCTA), Copenhagen, Aug. 2018, pp. 533–538.

Paper A presents a dynamical model that captures the multi-zone layout of a shopping center. The model is a grey-box RC-equivalent model suitable for both simulation experiments and model-based control designs. The paper presents the HVAC specifics of a section of *Kolding Storcenter*, a Danish mall, to which the model is fitted. Parameters for the model are estimated based on a combination of measurement data extracted from live operation of the shopping center and table-lookup. Paper A furthermore presents a preliminary high-level control design to minimize energy consumption spent on cooling, feeding back cooling valve opening degrees. The controller manipulates the forward temperature of a chiller to as high a temperature as possible, without saturating the valves.

Paper B

J. B. Petersen, J. D. Bendtsen, P. Vogler-Finck, and J. Stoustrup, “*Energy Flexibility for Systems with large Thermal Masses with Applications to Shopping Centers*,” in 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (Smart-GridComm), Aalborg, Oct. 2018, pp. 1–6.

Paper B builds on the work of Paper A, by using the proposed model in an MPC design to introduce energy flexibility using direct control. Paper B considers the same shopping center as in Paper A. The model is linearized and a standard MPC formulation is presented, where the cost is given as deviation from the chosen operating point. Energy flexibility is introduced as time-dependent constraints, dictating a specific energy consumption or power consumption, in a given time interval. The controller is evaluated in a simulation experiment, showing that a constraint on energy consumption over power consumption is better, as it infers integral action. The simulation results also show, that scaling up the results could provide power curtailments in the order of 100 kW for the entire shopping center, for a period of 1 h.

Paper C

J. B. Petersen, J. D. Bendtsen, and J. Stoustrup, “*Nonlinear Model Predictive Control for Energy Efficient Cooling in Shopping Center HVAC*,” in 2019 IEEE Conference on Control Technology and Applications (CCTA), Aug. 2019, pp. 611–616.

Paper C builds on Paper A, by using an extended version of the model in a Nonlinear Model Predictive Control (NMPC) design for more energy efficient operation of shopping center HVAC. The nonlinear model of the shop temperature dynamics is used directly in an optimal control problem that seeks to minimize cooling effort by manipulating with the operation of both an AHU and a chiller. The intention is to better coordinate the operation to avoid situations where the same air is both heated and cooled. This is achieved by moving cooling capacity from the chiller to the AHU, when free cooling is available through a low ambient temperature. The performance of the controller is evaluated in simulations and shows that significant energy savings can be obtained with no degradation of thermal comfort.

Paper D

J. B. Petersen, J. D. Bendtsen, A. G. Alleyne and J. Stoustrup, “*Low-Complexity Hierarchical Control for Distributed Shopping Center HVAC*,” in 21st IFAC World Congress, Jul. 2020.

Paper D presents an alternative control methodology for shopping center HVAC control. It presents a low-complexity hierarchical control approach that is less model-dependent than MPC, providing increased reusability and operator transparency. By applying the method to the same section of a shopping center as considered in Paper A, Paper B and Paper C, the method showed significant energy savings. The method was compared to a similar NMPC scheme as presented in Paper C. The comparison showed NMPC to be superior, which was expected – but that the lower-complexity method could recover 66 % of the performance.

Paper E

J. B. Petersen, J. D. Bendtsen, A. G. Alleyne and J. Stoustrup, “*A Simplified Hierarchical Approach to Distributed HVAC Control – a shopping center case study*,”, submitted for journal publication.

Paper E builds on the low-complexity hierarchical control approach in Paper D. It presents the steps taken to apply the method to a section of Kolding Storcenter, where it is used to control both an AHU and a chiller, coordinating production to meet the demand of the shops they supply. An experimental study is conducted, where the new controller is evaluated over a period from 9. November 2019 to 22. January 2020 – switching between the new controller and the baseline to allow for comparison in similar ambient conditions. Significant energy savings of 30 % to 40 % are demonstrated while not sacrificing thermal comfort.

Paper F

J. B. Petersen, J. D. Bendtsen, A. G. Alleyne and J. Stoustrup, “*Low-Complexity Hierarchical and Iterative Learning Control for Distributed HVAC*,”, submitted for journal publication.

Paper F generalizes the method presented in Paper E (originating in Paper D) and further enhances it by introducing ILC. An elaborate evaluation of both generality and performance is conducted, by investigating two case studies (shopping centers); CITY2 and Kolding Storcenter. For both case studies the generalized method is applied, ILC contribution is evaluated and overall performance is compared with MPC. For both case studies, the MPC is given ideal conditions as no model-mismatch is considered and perfect prediction is used. Results from using ILC show noticeable better tracking performance than when not using ILC in both case studies. Overall performance is compared on both energy consumption and thermal comfort, where the results show that MPC is best (as expected). However, the proposed method shows very similar results, recovering on average over 90 % of the MPC performance for both case studies. This makes it a viable alternative when considering building control retrofitting.

Chapter 1. Introduction

2 | Shopping center overview

The SEBUT project was introduced in **Section 1.3**, together with salient characteristics of shopping centers. This chapter further investigates shopping centers; both in terms of their energy consumption and their HVAC layout. This is done by looking at two Danish shopping centers involved in the SEBUT project.

2.1 Kolding Storcenter

Kolding Storcenter is a 51 388 m² large shopping center located in Kolding, Denmark. It was built in 1993 and expanded in 1999. A total of 120 shops occupy 38 358 m² ($\approx 75\%$) – besides shops, the shopping center houses 17 restaurants and a cinema. The floor plan is presented in **Figure 2.1**. The energy consumption is summarized in **Table 2.1**.

The cooling consumption is large, compared to the heating consumption. This is largely due to display lighting. It has been estimated that the heat gain from lighting is in the range 40 W/m² to 70 W/m² for the shops; this gives an internal heat gain when lights are on, in the range 1.5 MW to 2.7 MW.

Table 2.1: Kolding Storcenter energy consumption (2015)

	Heating	Cooling (electricity)
Annual (total)	2455 MW h	964 MW h
Annual (per m ²)	47.8 kW h/m ²	18.8 kW h/m ²

2.1.1 HVAC

The HVAC in Kolding Storcenter is inherently decentralized. Looking at **Figure 2.1**, each color coded area is supplied by its own rooftop AHU. In total, 17 rooftop AHUs supply the shops, 13 supply the common area, 3 supply the

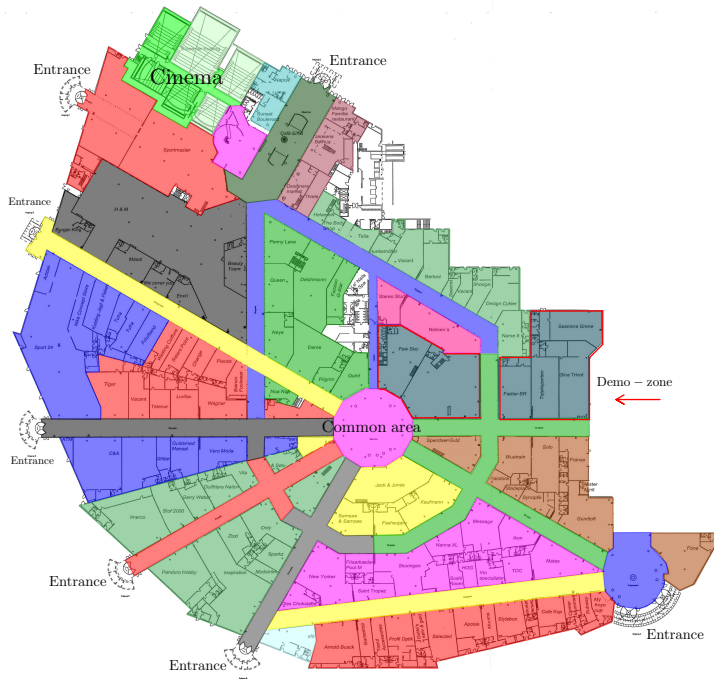


Fig. 2.1: Floor plan of Kolding Storcenter. Common area comprises hallways, center circle, around the large right-most entrance and around the two top entrances – near the cinema. Outlined in red is the demo-zone used in the SEBUT project.

cinema and 1 supplies office space. No shops feature natural ventilation (e.g. using windows), only the common area has natural ventilation. The annual electricity consumption spent on ventilation is 1300 MWh. The AHUs can both heat and cool the supply air. Different types are installed; the newest 14 (6 supplying shops) can heat and cool using a built-in heat pump and a rotary heat exchanger. The oldest provide cooling using direct expansion.

Cooling is equally decentralized with 18 rooftop chillers, of which 17 supply shops and 1 supplies the cinema. Groups of shops, color coded in **Figure 2.1** are thus supplied by their own rooftop AHU and their own rooftop chiller. The combined cooling capacity of the rooftop chillers is 3.5 MW. With cooling capacity available through the AHUs as-well, this should be plenty when considering the lighting heat gains. Heating is by district heating and through the AHUs by heating the supply air using the rotary heat exchanger, or in rare cases the heat pump. The heating consumption in **Table 2.1** is only district heating.

Ventilation, cooling and heating is supplied through ceiling mounted Fan Coil Units (FCU) in each shop. The same FCUs are used in all shops,

2.1. Kolding Storcenter

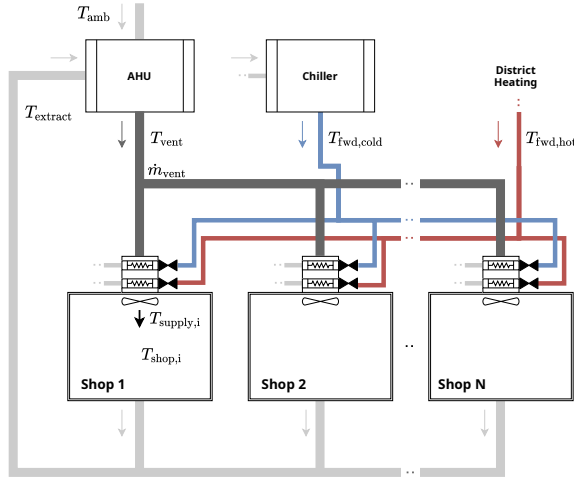


Fig. 2.2: Decentralized HVAC layout for cluster of shops in Kolding Storcenter. Shops are clustered by which AHU and chiller pair that supplies them.

with on average 0.8 FCU per 100 m². FCUs and AHUs are operated in a Constant Air Volume (CAV) manner; the flow is constant when ventilation is ON. Each FCU has both a cooling and a heating coil with valves governing the flow through the coils. The valves are controlled by a zone (or shop) temperature control scheme. The FCUs feature recirculation of the air, so that not 100% of the supply flow is from the AHU, but a ratio is extract air from the shops.

The HVAC layout in Kolding Storcenter is depicted in **Figure 2.2**. This corresponds to the HVAC layout for one of the colored areas in **Figure 2.1**.

2.1.2 Operation and control

The HVAC operates according to a schedule set by the building operators. The schedule determines when the AHUs are ON, when the chiller is ON, when the FCUs are ON. The schedule is depicted in **Figure 2.3** and also shows shop opening hours.

When ON, the AHUs are operated using extract air temperature control, where the extract air is the air extracted from the shops (return air). A building operator can specify an extract air temperature setpoint and the internal control in the AHU will attempt to regulate the amount of heating and cooling to achieve the desired extract air. The extract air control is further discussed in **Section 3.2.2**.

The chiller forward temperature is controlled internally and a setpoint is not exposed to the BMS. Instead, an operator chooses an operating mode,

either *ON*, *OFF* or *AUTO*. Where *AUTO* is following the set operator given time schedule. A circulation pump maintains a constant pressure differential. Heating from district heating is only enabled when the outside temperature drops below 16 °C.

The FCU control is a cascade controller, depicted in **Figure 2.4**. An outer-loop shop temperature controller, measuring shop temperature and deciding a desired supply temperature controller. An inner-loop supply temperature controller, measuring FCU supply temperature (into shops) and determining valve opening degrees for heating and cooling coils. Both controllers have been identified as PI controllers. The shop temperature setpoint is a combination of a setpoint specified by a building operator and an adjustment value, specified in the shops using a physical dial/knob.

Very few shops are directly adjacent to the ambient and none of the shops feature windows. Hence, shop temperature is not very dependent on either ambient temperature or solar load – but mainly dependent on internal heat gain (lighting) and the temperature of the common areas.

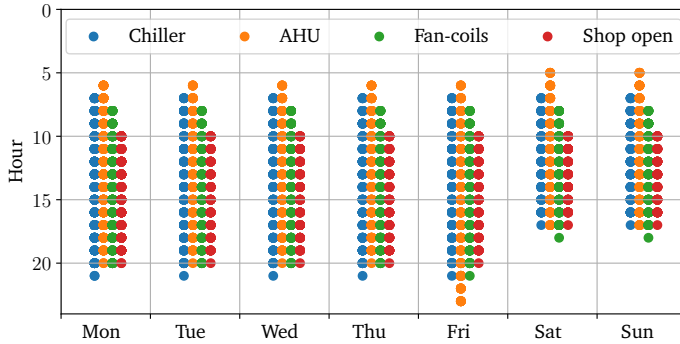


Fig. 2.3: HVAC operation schedule and shop opening hours in Kolding Storcenter.

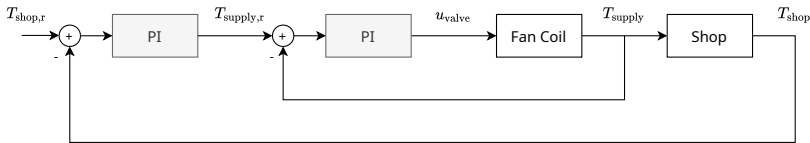


Fig. 2.4: Shop temperature control in Kolding Storcenter.

2.1.3 Demo-zone

During the SEBUT project a demo-zone was established. This demo-zone is depicted in **Figure 2.1**. The demo-zone is chosen as the shops supplied by a specific AHU and chiller pair. In total, six shop leases are covered by this

2.2. CITY2

AHU and chiller pair. Of these six, three were more thoroughly investigated in the SEBUT project. **Section 3.2** gives an account of how instrumentation in the demo-zone was made available.

2.2 CITY2

CITY2 is a 94 888 m² large shopping center located in Høje Taastrup, Denmark. It was built in 1974 and houses 80 shops on 55 000 m² ($\approx 60\%$), leaving approximately 40 000 m² for common area. Compared to Kolding Storcenter, CITY2 is larger and in three stories but with fewer larger leases and more common area. A floorplan is presented in **Figure 2.5** and the energy consumption is summarized in **Table 2.2**.

Compared to Kolding Storcenter, the heating consumption is significantly higher and the cooling consumption significantly lower. With the same estimated heat gains in shops, the large difference is most likely attributed to a lower level of insulation, given that CITY2 is approximately 20 years older.

Table 2.2: CITY2 energy consumption (2013)

	Heating	Cooling (electricity)
Annual (total)	5946 MW h	274 MW h
Annual (per m ²)	62.7 kW h/m ²	2.9 kW h/m ²

2.2.1 HVAC

The HVAC in CITY2 can also be described as decentralized, but is very different than in Kolding Storcenter. The common area is supplied by 6 large AHUs while the shops are supplied by 18 AHUs in different sizes; some supplying up to 11 shops while others only supply a single shop. Only the common area features natural ventilation (by opening windows). All the AHUs are placed in the basement of the building, where they are grouped into different rooms. Some rooms with up to 4 AHUs others with only a single one. The rooms make it out as a mixing chamber, mixing fresh air with extract air for recirculation. The AHUs supplying the common area have both a heating coil and a cooling coil while it varies for the AHUs supplying shops – some have both a heating and a cooling coil, some have only a cooling coil and others only a heating coil. This setup is depicted in **Figure 2.6** which shows the HVAC diagram for one mixing chamber and the AHUs placed in it.

Cooling is, compared to Kolding Storcenter, central, with one large cooling plant made up of two large cooling units. This cooling plant serves all the



Fig. 2.5: Floor plan of CITY2, only showing the main floor. The uppermost floor has shops as well, while the bottom floor features a fun center.

AHUs. A newer (2016), smaller unit with a cooling capacity of 900 kW and a larger older (2000) unit with a cooling capacity of 1800 kW for a combined cooling capacity of 2.7 MW. Heating is by district heating, through a heat exchanger, which feeds all the AHUs.

The terminal units in CITY2 are very different to the FCUs in Kolding Storcenter. They are also CAV, but compared to Kolding Storcenter they only feature limited possibility for local heating or cooling of the supply air. Many different types have been recorded in the different shops, as they have been replaced over the years. This means that the shop-local temperature control is highly dependent on the supply temperature from the AHUs, as there is limited capacity for changing it.

Very few shops are directly adjacent to the ambient and they do not feature windows. This means that shop temperature is not very dependent on either ambient temperature or solar load. Instead shop temperature is highly dependent on internal heat gain and the temperature of the common area.

2.2. CITY2

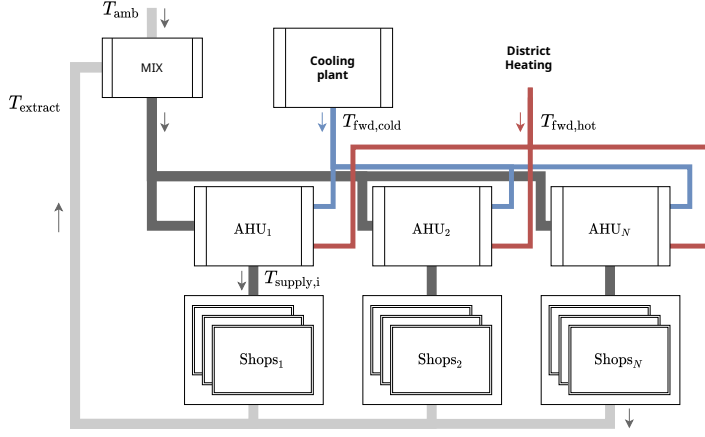


Fig. 2.6: Decentralized HVAC in CITY2, showing AHUs and their shared mixing chamber (the room in which they are placed). Cooling is supplied from a central cooling plant and heating from district heating. Not all AHUs have both heating and cooling coils as depicted here.

2.2.2 Operation and control

The HVAC operates according to a schedule set by the building operators, determining when AHUs are ON and when the cooling plant is ON. The schedule is depicted in **Figure 2.7** which also shows shop opening hours.

The AHUs are operated using supply air temperature control. Some AHUs have been identified to also use extract air (return air) temperature control, but this controller will just be governing the underlying supply air temperature control. Setpoints are specified by the building operators. The controllers then manipulate valve openings for cooling and heating coils to achieve desired temperature.

Cooling is released when the ambient temperature, T_{amb} , is above 16°C . The forward temperature control is shared between the two cooling units, regulating to the same forward temperature, $T_{fwd,cool}$. The setpoint, $T_{fwd,cool,r}$ is determined by a setpoint curve:

$$T_{fwd,cool,r}(T_{amb}) = -0.55 T_{amb} + 23.3^\circ\text{C} \quad (2.1)$$

Heating is also controlled by a setpoint curve, determining forward temperature, $T_{fwd,heat}$ based on ambient temperature:

$$T_{fwd,heat,r}(T_{amb}) = -2.55 T_{amb} + 67.5^\circ\text{C} \quad (2.2)$$

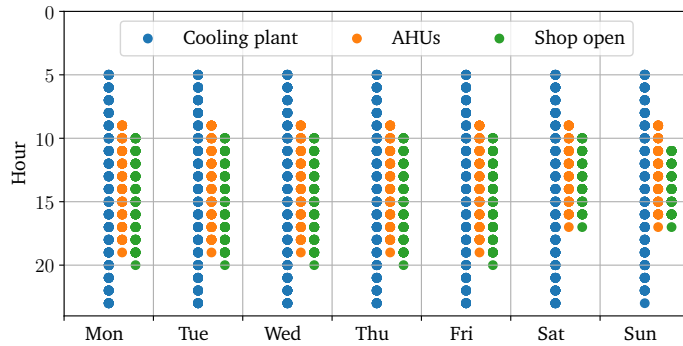


Fig. 2.7: HVAC operation schedule and shop opening hours in CITY2. Note that the cooling plant is not ON in all of the given hours, but that it is allowed to be ON in those hours.

2.2.3 Demo-zone

Just as for Kolding Storcenter, a demo-zone was established in CITY2. The CITY2 demo-zone was selected by focusing on one mixing chamber and the AHUs that share this mixing chamber. The specific mixing chamber has four AHUs; one AHU supplying 3 shops, one AHU supplying 4 shops, one AHU supplying 2 shops and the last AHU only supplying 1 shop.

3 | Facilitating control of buildings

As introduced in **Section 1.2**, the climate control of larger buildings is handled by a BMS; the equivalent of a Supervisory Control and Data Acquisition (SCADA) for buildings. To implement new building control for existing buildings there are two options. The BMS can be replaced with a new BMS. This can be a relatively expensive option, as replacing a BMS is typically not limited to a simple software upgrade. A BMS is a complete hardware and software system, potentially involving both proprietary control units, sensors and actuators. The other option is by interfacing with the existing BMS. This chapter treats how it is possible to interface with an existing BMS by introducing the BMS landscape and presenting a case study on how this was achieved in the SEBUT project. The chapter concludes with a discussion and outlook.

3.1 Interfacing with Building Management Systems

Interfacing with an existing BMS is only possible if said BMS communicates using an open protocol. This can be a hit-and-miss endeavor, as the building communication protocol landscape is fragmented and historically dominated by proprietary solutions[52]. In [52] (2005), the authors discuss how *open* systems and standards play a key role in the building automation domain. They introduce the three main open standards for BMS-wide communication:

BACnet The Building Automation and Control Networking Protocol. Developed to meet needs within building control. First published as an ASHRAE/ANSI standard in 1995.[53]

LonWorks is designed as a *generic control network*. Published as a standard in 1999.[54]

KNX is coined as a *home and building electronic system* standard. Originated as the European Installation Bus (a fieldbus), later KNX (2002).[55]

While these three are the main open standard for BMS-level, it is worth mentioning, that Modbus also plays a significant role in building control networks, especially within the control of e.g. Rooftop Units (RTUs). While never standardized, Modbus is definitely characterized as open.

The landscape has however changed since the authors of [52] did their review of communication systems for building automation and control. As of 2018 it was estimated that BACnet global market share had exceeded 60 % and is still growing[56].

If a BMS relies on open standards for its communication, it enables *piggybacking* as a way to undertake building control retrofitting. The concept is depicted in **Figure 3.1**. Looking at the conceptual BMS network in **Figure 3.1** there are two levels where it is possible to intervene, given the communication is open. Either at the management level or at the automation level – or a combination. If a new controller was placed at the management level, one could imagine the possibility of manipulating with schedules and setpoints in the same manner as a human operator. Placing a controller on the automation level might allow for more fine-grained control in the case that e.g. not all setpoints and sensor measurements are propagated to the management level.

Doing a building control retrofit using piggybacking is on the premise of the existing infrastructure. As a control engineer, one does not get to pick and choose; one has to adapt to what is already available and perhaps has to rely on re-programming parts of the BMS in the case of sparse/limited options for control inputs and available measurements. Where a regular control design may carefully select which sensors and actuators to include, in a retrofit case this has already been done and one has to figure out whether it is possible to improve the building control significantly using **just** what is available. Additional BMS programming efforts may also be needed in the case of e.g. conflicting writes to a setpoint.

One common issue, which is not specific to building control retrofitting but also prominent in process control in general, is that of *tagging*. A tag refers to the name of a signal/entity. This tag, often the only description of the signal, has to encapsulate information about function, type, position etc. Depending on the scale of the application, tagging conventions can be quite sophisticated and consistent. But they can equally be inadequate, making it a labor intensive manual effort for a trained professional to retrieve necessary metadata from an existing BMS installation. This can potentially make a retrofit application intractable[57]. Effective metadata schemas is an active research topic within building control as presented in [58], but this does not solve the tagging issues for the existing building stock. Instead, automated mapping could be a solution as treated in [59, 60]. But as concluded in [59], a practical solution to automated mapping, which handles both type classification (e.g. temperature sensor, fan speed), location identification (e.g. spe-

3.1. Interfacing with Building Management Systems

cific AHU, specific fan-coil unit), identification of functional relationship (e.g. AHU 3 supplying fan-coil unit 23) and identification of spatial relationship (e.g. temperature sensor in room 22) does not exist yet.

In [13] the specifics of how the authors interface with the BMS are not given, but they state that they retrieve measurements from the BMS and apply new setpoints into the BMS. In [14] the authors installed a commercial embedded devices, acting as a gateway between the BMS network and the author's control software. In [15] the authors rely on a File Transfer Protocol (FTP) server for pushing and pulling data to the BMS. This FTP server was setup by the BMS provider. In [16] the authors install a parallel commercial SCADA solution, communicating with the existing BMS using Modbus. The installed SCADA exposes an internet-accessible Application Programming Interface (API) for retrieving and setting setpoints. In [18] the authors install a new PC in the building, with their control software. The PC is connected to the BACnet BMS network at management level.

All of the examples from the literature use some form of piggybacking on the existing BMS, but there is no standard way of doing building control retrofitting.

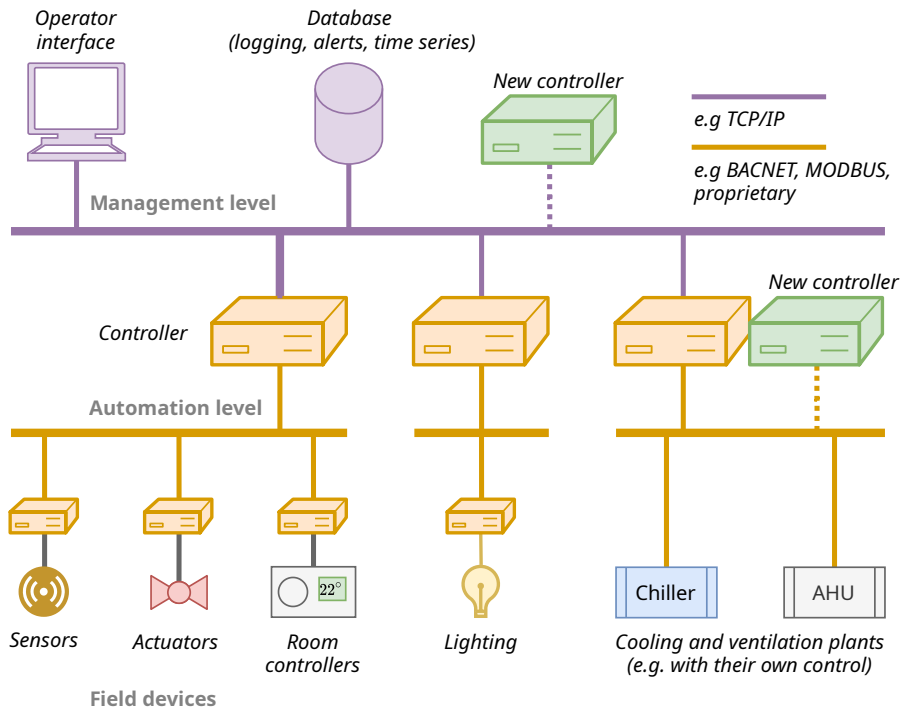


Fig. 3.1: Depicting potential BMS piggybacking. Either the addition of a new controller at management level or at automation level.

3.2 Case study

This section presents how interfacing with an existing BMS was handled within the work of this thesis and the SEBUT project. The case studied is Kolding Storcenter, which is presented in **Section 2.1**. The section includes an account of a proof-of-concept control demonstration.

The whole shopping center is not considered, but only a group of shops and the AHU and chiller supplying these are considered. The reduced BMS network for this case is depicted in **Figure 3.2** – together with the practical control interventions made. Looking at **Figure 3.2** the BMS network is divided into two branches; one for shops and one for AHUs and chillers. The shop-branch is communicating using BACnet (Master-Slave, Twisted-Pair). The communication is relayed to the management level (TCP/IP) through a single controller (*shop controller*) unit that is connected to both to the twisted-pair network and to the TCP/IP network. The HVAC branch (AHU and chiller) is communicating using a proprietary protocol; Trend LAN[61]. The communication is relayed to the management level using a single controller (*HVAC controller*).

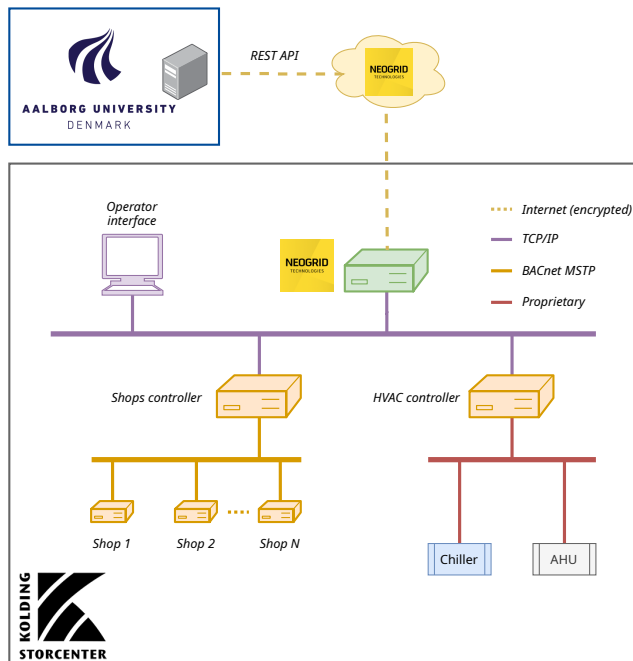


Fig. 3.2: The BMS communication layout for a part of Kolding Storcenter. Also depicted is how a Neogrid Technologies gateway is used to interface with the existing BMS, allowing for developing and testing control solutions on hardware located off-site; as in this case at Aalborg University.

3.2.1 Interventions

Neogrid Technologies is a project partner in the SEBUT project. They provide intelligent buildings control relying on a piggyback approach. They provide a *gateway* unit; a piece of hardware that can be connected to an existing building control network (BACnet, Modbus) and facilitate instrumentation using a cloud solution. They allow logging available measurements to their cloud infrastructure and expose both measurements and the possibility of applying new controls (e.g. new setpoints) through a REpresentational State Transfer (REST) API.

A Neogrid Technologies gateway is connected as depicted in **Figure 3.2**. The actual physical gateway placed in Kolding Storcenter is shown in **Figure 3.3a**. For the AHU and chiller, it required reprogramming of the HVAC controller to expose signals using BACnet instead, as it was currently only communicating using the proprietary Trend LAN. It was a non-issue to establish the possibility of logging measurements from the shops, given that this branch of the network uses BACnet. Mapping available signals was possible using their tags and using metadata information encoded in the BMS Graphical User Interface (GUI) – see example in **Figure 3.3b**.

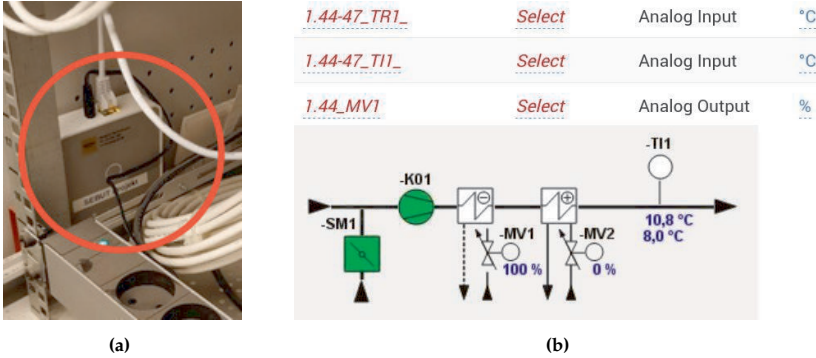


Fig. 3.3: **a** Neogrid Technologies gateway connected to BMS network in Kolding Storcenter.
b Example of tags and metadata available through BACnet and BMS GUI.

3.2.2 Proof-of-concept control

To demonstrate the potential of BMS control interventions, a proof-of-concept controller was developed and tested. As is, the AHUs in Kolding Storcenter are controlled by setting a constant air flow setpoint and an extract air temperature setpoint, $T_{\text{extract},r}$. Disregarding the air flow aspect, a simplified control diagram of the system is given in **Figure 3.4**. The AHU features extract air temperature control, actuating available heating and cooling to manipulate AHU supply temperature, T_{vent} . This changes shop temperatures, and

hence also the extract air temperature, over time. Extract air temperature control is a common control option for AHUs and can be a good option if the AHU is the only unit responsible for space heating/cooling. In a more complex HVAC configuration, it can be more attractive to directly command supply air temperature.

Therefor, the goals of the proof-of-concept controller is to *reconfigure* the AHU controls from extract air temperature control to supply temperature control. This is thought possible by decoupling the existing controls through a new controller in parallel (see **Figure 3.4**). The new controller interfacing with the existing BMS. The stability and robustness of this reconfiguration depends highly on the complexity of the extract temperature control – if it is riddled with rule-based control and logic expressions this is non-trivial.

In this proof-of-concept, the new controller was chosen as a proportional controller for simplicity. This new controller was implemented on a PC at Aalborg University, using the API provided by Neogrid Technologies to facilitate extraction of measurements and applying new control signals. The sampling time is 5 min, a constraint set by the Neogrid Technologies infrastructure.

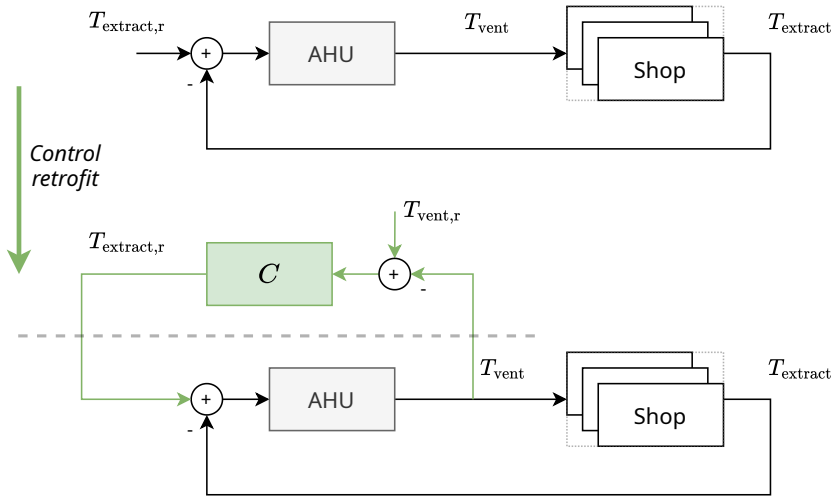


Fig. 3.4: Simplified control diagram of AHU control in Kolding Storcenter, disregarding air flow. Top is existing control, bottom is after retrofit, interfacing with the existing BMS.

An experiment was conducted to show the feasibility of this control retrofit. In the experiment, different supply temperature setpoints are commanded over the course of one day. The extract air temperature setpoints are manipulated, as this is now the control input. The existing control logic drives the rotary heat exchanger in response to the new extract air tempera-

points, which changes the heat input. The results from the experiment are shown in **Figure 3.5**. The results show, that it is possible to introduce supply temperature control on top of existing extract air temperature control, as setpoints are successfully met.

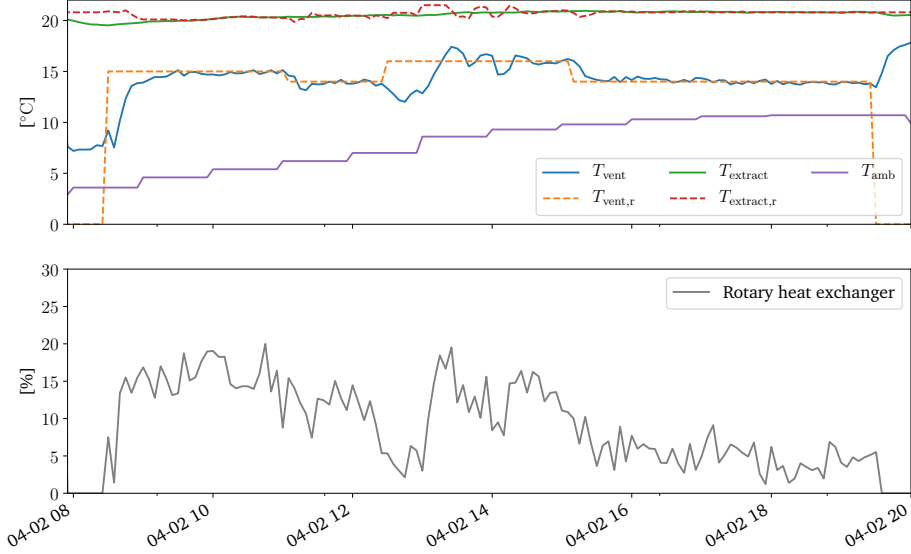


Fig. 3.5: Experimental results showing how an extract air temperature controlled AHU can be retrofitted to do supply temperature control, by interfacing with the existing BMS, manipulating the setpoint to the extract air temperature controller. The supply temperature follows the given setpoints.

3.3 Discussion

The case study (Kolding Storcenter) together with the control example presented in this chapter demonstrates both pros and cons of the approach. The pros being reduced cost by recycling existing infrastructure and *plug-n-play* properties. The cons being that not all existing BMS installation feature open protocols, which is a significant barrier. The pros are however further emphasized in **Paper E**. Here a hierarchical controller is demonstrated in Kolding Storcenter through a control experiment from November 2019 to January 2020, seamlessly switching between using the new hierarchical controller and the already existing control. Manipulating with only three setpoints, savings of 30 % to 40 % are achieved, simply by limiting over-ventilation and introducing coordination between supply and demand of heating and cooling.

Even with the known barriers, the author of this thesis highly encourages the pursuit of a piggybacking-approach to improve energy efficiency

in the existing building stock, including shopping centers. The author also highly encourages the choice of both BMS and general HVAC equipment that support open protocols, as this will be the limiting factor when considering energy refurbishments through control applications in the future.

4 | Modeling shopping center temperature dynamics

This chapter introduces the work done to establish a model of temperature dynamics in a shopping center. A model of the dynamics of a system is a key part in modern control engineering. It serves the purpose of allowing simulations to not only rely on experimental tests; this is very important given the difficulty of emulating the specifics of a shopping centers dynamics in an existing laboratory setup, reducing options for test to be either simulation or a full-scale experiment. A model of the dynamics is also an integral part in a model-based control design. In an MPC design, an accurate model is a necessity and often the most time-consuming part, as discussed in **Section 1.2**.

Often a distinction is made between a *simulation model* and a *control-oriented model*. As the main purpose of the simulation model is to mimic the real-world system, the main requirement is accuracy – the model has to fit so well, that when evaluating a new control design in simulations, conclusions can be drawn for the real-world case as well. As accuracy increases, so does complexity – if the system itself is complex. This is a non-issue for a simulation model of a building, given the amount of computational resources available today. It is only limited by the cost of engineering effort.

The main purpose of the control-oriented model, is to exhibit dynamics similar enough to the real-world system, so that a model-based control design will benefit. The accuracy requirement is thus less strict, and merely has to be *good enough*. From the literature introduced in **Section 1.2**, the most prominent control-oriented model approach for multi-zone building control is an RC-equivalent grey-box modeling approach[20]. The benefit being that the approach is a hybrid between first-principles physics-based analytical models (white-box) and purely statistics/data-driven models (black-box).

Given the scope of the project, only effort towards RC-equivalent grey-box control-oriented models has been made and these models have been used for both simulations and model-based control designs. One important caveat is, that the models have been posed on the basis of what information was available by interfacing with the BMS as treated in **Chapter 3**.

Given the aim of posing models usable for both simulation and model-based control designs, a simulation environment based on *CasADi*[62] was built. *CasADi* is a tool for algorithmic differentiation and nonlinear optimization. It allows posing symbolic equations from which both gradients, Jacobians and Hessians can be extracted. Encompassing the idea of using the same models for simulation and control, *CasADi* allows posing the dynamics **once** and then perform both simulation studies of the pure dynamics – or incorporate the dynamics in an optimal control problem for e.g. MPC applications. The control part is covered in **Chapter 5**.

4.1 Multi-zone model

A shopping center is a multi-zone commercial building. The multi-zone characteristics means that multiple thermal *zones* are interacting with each other. A natural choice is that each zone is a shop. This choice may not always be suitable if a shop is so large, so that different temperature dynamics can be observed in different areas within the shop. This could be the case if air flow is blocked by the interior design (different sections in a shop) or if one part of the display lighting has been exchanged to LED while another is halogen or incandescent light bulbs. However, the i -th zone temperature is denoted as $T_{\text{shop},i}$ as it is assumed that most shops can be described by a single thermal zone.

The thermal dynamics of a single shop is given by:

$$C_{\text{shop},i} \dot{T}_{\text{shop},i} = \dot{Q}_{\text{HVAC},i} + \dot{Q}_{\text{adjacent},i} + \dot{Q}_{\text{int},i} \quad (4.1)$$

where $C_{\text{shop},i}$ is the lumped thermal capacitance, covering the thermal capacity of the air, walls, interior, etc. The heat balance is governed by three heat flows; $\dot{Q}_{\text{HVAC},i}$ which is heat flow due to HVAC, $\dot{Q}_{\text{adjacent},i}$ which is heat flow to adjacent thermal zones and $\dot{Q}_{\text{int},i}$, which is internal heat gain. The internal heat gain is occupancy, appliances and especially lighting. As made apparent in **Chapter 2**, shops are often not exposed to direct sunlight and they often do not have walls in direct contact with the ambient. This means that shop temperatures are largely independent of the ambient conditions. This does not mean, that shop temperatures are not influenced by seasonal weather changes. The shop temperatures are dependent on the overall shopping center temperature (e.g. common area), which will have an influence through $\dot{Q}_{\text{adjacent},i}$. Weather effects are thus low-pass filtered through the common area and other thermal zones. The common area can equally be considered as made up of different thermal zones with temperature $T_{\text{common},i}$, e.g. different sections of hallway area. The difference to $T_{\text{shop},i}$ is that $T_{\text{common},i}$ will

4.1. Multi-zone model

often be influenced more greatly by the ambient conditions:

$$C_{\text{common},i} \dot{T}_{\text{common},i} = \dot{Q}_{\text{HVAC},i} + \dot{Q}_{\text{adjacent},i} + \dot{Q}_{\text{int},i} + \dot{Q}_{\text{amb},i} \quad (4.2)$$

where $\dot{Q}_{\text{amb},i}$ is heat flow to/from the ambient. As a general notation, T_i is zone temperature of either a shop thermal zone ($T_{\text{shop},i}$) or common area thermal zone ($T_{\text{common},i}$).

Heat exchange between adjacent zones can be assumed to only be resistive, given that inner walls are often very thin and thus do not store appreciable amounts of heat:

$$\dot{Q}_{\text{adjacent},i} = \sum_{j \in \mathcal{N}_i} \frac{T_j - T_i}{R_{i,j}} \quad (4.3)$$

where \mathcal{N}_i is the set of zones adjacent to i , T_i is either $T_{\text{shop},i}$ or $T_{\text{common},i}$ and $R_{i,j}$ is the thermal resistance between the two zones.

For both shopping centers presented in **Chapter 2**, the main HVAC contribution to shops and common area is through the supply of heated or cooled air, letting $\dot{Q}_{\text{HVAC},i}$ be described as:

$$\dot{Q}_{\text{HVAC},i} = \dot{m}_{\text{air},i} c_{p,\text{air}} (T_{\text{supply},i} - T_i) \quad (4.4)$$

where $\dot{m}_{\text{air},i}$ is the mass flow of air, $c_{p,\text{air}}$ is specific heat capacity of air and $T_{\text{supply},i}$ is the supply air temperature.

To potentially encompass an entire shopping center with hundreds of thermal zones, the expressions have been formulated using a graph-theoretical view. Collecting all thermal zones as nodes in the graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, where \mathcal{N} is the set of all nodes and \mathcal{E} the set of all edges. An edge in the graph describes that two zones are physically adjacent. If the edge is weighted by $G_{i,j} = 1/R_{i,j}$ (thermal conductance), the adjacency matrix is given by:

$$\mathbf{A}(\mathcal{G}) = [a_{i,j}] = [G_{i,j}] \in \mathbb{R}^{N_{\text{zones}} \times N_{\text{zones}}} \quad (4.5)$$

Letting $d(i) = \sum_j G_{i,j}$ be the degree of node i and $\mathbf{D}(\mathcal{G}) = \text{diag}(d(i))$, the Laplacian matrix of \mathcal{G} can be computed as:

$$\mathbf{Q}(\mathcal{G}) = \mathbf{D}(\mathcal{G}) - \mathbf{A}(\mathcal{G}) \quad (4.6)$$

The heat exchange between adjacent zones can now be collected in a vector:

$$\dot{\mathbf{Q}}_{\text{adjacent}} = -\mathbf{Q}(\mathcal{G}) \mathbf{T} \quad (4.7)$$

$$\mathbf{T} = [T_i]^T = [\mathbf{T}_{\text{shop}}^T \quad \mathbf{T}_{\text{common}}^T]^T \quad (4.8)$$

where $\mathbf{T}_{\text{shop}} \in \mathbb{R}^{N_{\text{shops}}}$ and $\mathbf{T}_{\text{common}} \in \mathbb{R}^{N_{\text{common}}}$ are the column vectors collecting all the shop zone temperatures and common area zone temperatures,

respectively. With this result, we can reduce our state equations to:

$$\mathbf{C} \dot{\mathbf{T}} = -\mathbf{Q}(\mathcal{G}) \mathbf{T} + \dot{\mathbf{Q}}_{\text{HVAC}} + \dot{\mathbf{Q}}_{\text{int}} \quad (4.9)$$

$$\dot{\mathbf{Q}}_{\text{HVAC}} = \dot{\mathbf{M}}_{\text{air}} c_{p,\text{air}} (\mathbf{T}_{\text{supply}} - \mathbf{T}) \quad (4.10)$$

where $\mathbf{C} \in \mathbb{R}^{N_{\text{zones}} \times N_{\text{zones}}}$ is a diagonal matrix with $C_{\text{shop},i}$ and $C_{\text{common},i}$ in the diagonal and $\dot{\mathbf{M}}_{\text{air}} \in \mathbb{R}^{N_{\text{zones}} \times N_{\text{zones}}}$ is a diagonal matrix with $\dot{m}_{\text{air},i}$ in the diagonal.

The multi-zone model is in **Paper A** successfully applied to a section of the SEBUT demo-zone in Kolding Storcenter, depicted in **Figure 4.1**. One thing to note is, that applying the multi-zone model revealed that heat exchange between adjacent zones may be disregarded. As internal heat gain dominates the heat balance, the adjacency term can become negligible. The internal heat gain due to lighting is in Kolding Storcenter estimated as 40 W/m^2 to 70 W/m^2 , giving 10.0 kW to 17.5 kW for a shop that is 250 m^2 . In **Paper A** the thermal conductance between zones is, by table-lookup[20], determined to be in the range 50 W/K to 100 W/K . For a (relatively high) temperature difference of 5 K , this is 250 W to 500 W . Had the lighting been LED, the heat gain would instead be in the order 5 W/m^2 to 10 W/m^2 , giving 1.25 kW to 2.50 kW – which would no longer render the adjacency term negligible.

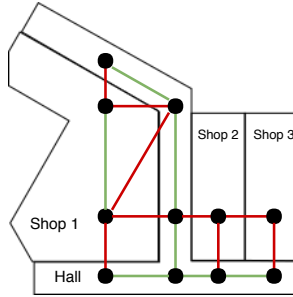


Fig. 4.1: Section of Kolding Storcenter demo-zone where multi-zone model is applied. The graph is depicted as an overlay on the floor plan of the section. Different color edges determine different thermal resistances; green indicates no wall and yellow indicates a wall/barrier[63].
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4.2 Decentralized HVAC and Fan Coil Units

One example of a shopping center HVAC system is Kolding Storcenter, which features both decentralized ventilation and cooling, delivered to all shops through FCUs. A significant effort has through the project been put into posing a model that captures the main dynamics of such a HVAC system. Models of the HVAC system in Kolding Storcenter originates in **Paper A**

4.2. Decentralized HVAC and Fan Coil Units

(only cooling) and have been presented in slightly different editions through **Paper B** (cooling and heating), **Paper C** (ventilation, cooling and heating), **Paper D** (ventilation, cooling and heating) and **Paper F** (ventilation, cooling and heating). This section summarizes the work.

The model relates to the HVAC diagram depicted in **Figure 4.2**.

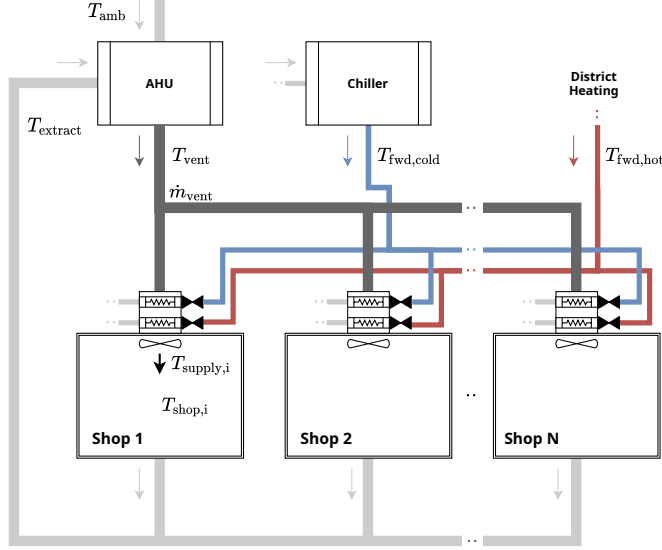


Fig. 4.2: HVAC layout in Kolding Storcenter. Decentralized AHUs and chillers feed FCUs in shops. FCUs allow for temperature regulation of the shops.

A simplification is made, so that each shop zone can only have one FCU in the model. In reality, each shop has several FCUs – but in the BMS, they are seen and controlled as a single large FCU. Hence, the index i always relates to the same shop, whether the index is used for the FCU dynamics or the shop temperature dynamics.

The supply temperature dynamics for the i -th shop and FCU are modeled as:

$$C_{\text{supply},i} \dot{T}_{\text{supply},i} = \dot{Q}_{\text{AHU},i} + \dot{Q}_{\text{FC-amb},i} + \dot{Q}_{\text{cool},i} + \dot{Q}_{\text{heat},i} - \dot{Q}_{\text{FC},i} \quad (4.11)$$

where $C_{\text{supply},i}$ is a lumped thermal capacitance for the FCU, $\dot{Q}_{\text{AHU},i}$ is heat flow from AHU to FCU and $\dot{Q}_{\text{FC-amb},i}$ is loss from FCU to the surroundings. The terms $\dot{Q}_{\text{cool},i}$ and $\dot{Q}_{\text{heat},i}$ are heat flows from cooling and heating coils in the FCU to the supply air. The final term, $\dot{Q}_{\text{FC},i}$, is heat flow from FCU to the shop.

Heat flow from AHU to FCU is given by:

$$\dot{Q}_{\text{AHU},i} = \dot{m}_{\text{FC},i} c_{p,\text{air}} (T_{\text{vent}} - T_{\text{supply},i}) \quad (4.12)$$

with $\dot{m}_{FC,i}$ being mass flow of air from AHU to FCU – and consequently from FCU to the shop. Temperature of the supply air from the AHU is denoted T_{vent} .

Heat flow from FCU to surroundings, $\dot{Q}_{FC-amb,i}$ is given by:

$$\dot{Q}_{FC-amb,i} = \frac{1}{R_{FC-amb,i}} (T_{center} - T_{supply,i}) \quad (4.13)$$

where $R_{FC-amb,i}$ a thermal resistance. The surroundings are given the general shopping center temperature, T_{center} .

Heat flow from cooling and heating coils are modeled as:

$$\dot{Q}_{cool,i} = u_{cool} \alpha_{cool,i} u_{valve,cool,i} c_{p,water} (T_{fwd,cool} - T_{supply,i}) \quad (4.14)$$

$$\dot{Q}_{heat,i} = u_{heat} \alpha_{heat,i} u_{valve,heat,i} c_{p,water} (T_{fwd,heat} - T_{supply,i}) \quad (4.15)$$

Here u_{cool} and u_{heat} are activation signals, in principle determining whether the circulation pumps are ON (1) or OFF (0). The parameters, $\alpha_{cool,i}$ and $\alpha_{heat,i}$ cover both coil efficiency and valve characteristics. The valve opening degrees are given by $u_{valve,cool,i}$ and $u_{valve,heat,i}$. The forward temperature from the chiller is given by $T_{fwd,cool}$ and the forward temperature from district heating by $T_{fwd,heat}$.

As described in **Section 2.1**, the valve openings are governed by cascaded PI controllers (**Figure 2.4**). A shop temperature PI controller which manipulates a setpoint to supply temperature, $T_{supply,r,i}$, and a supply temperature PI controller which manipulates valve openings, $u_{valve,cool,i}$ and $u_{valve,heat,i}$. These are modeled as:

$$\dot{T}_{supply,r,i} = -K_{p,shop,i} \dot{T}_{shop,i} + K_{i,shop,i} (T_{shop,r,i} - T_{shop,i}) \quad (4.16)$$

$$\dot{u}_{valve,i} = -K_{p,supply,i} \dot{T}_{supply,i} + K_{i,supply,i} (T_{supply,r,i} - T_{supply,i}) \quad (4.17)$$

$$u_{valve,cool,i} = \max\{-u_{valve,i}, 0\} \quad (4.18)$$

$$u_{valve,heat,i} = \max\{u_{valve,i}, 0\} \quad (4.19)$$

where K_p is the proportional gain and K_i the integral gain. The combined valve opening signal, $u_{valve,i}$, is negative for an open cooling valve and positive for an open heating valve.

For the AHU, the temperature dynamics of T_{vent} are modeled, by letting a PI controller govern the heat balance:

$$C_{AHU} \dot{T}_{vent} = u_{AHU} \dot{Q}_{AHU} + \dot{Q}_{AHU-amb} \quad (4.20)$$

$$\dot{V}_{AHU} = -K_{p,AHU} \dot{T}_{vent} + K_{i,AHU} (T_{vent,r} - T_{vent}) \quad (4.21)$$

$$V_{AHU} = \dot{Q}_{AHU} \quad (4.22)$$

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where u_{AHU} determines whether the AHU is ON (1) or OFF (2). The heat loss to ambient, $\dot{Q}_{\text{AHU-amb}}$, is modeled as:

$$\dot{Q}_{\text{AHU-amb}} = \frac{1}{R_{\text{AHU-amb}}} (T_{\text{amb}} - T_{\text{vent}}) \quad (4.23)$$

Hence, the specifics of the AHU are not modeled but covered by an abstraction.

The general shopping center temperature, T_{center} is modeled as:

$$\dot{T}_{\text{center}} = \tau_{\text{extract}} (T_{\text{extract}} - T_{\text{center}}) + \tau_{\text{amb}} (T_{\text{amb}} - T_{\text{center}}) \quad (4.24)$$

with T_{extract} being the extract air temperature for the AHU.

The model is summarized in **Figure 4.3**, showing the classification of the above model variables in states and inputs. The classification of controllable inputs is in the context of Kolding Storcenter – knowing what can be manipulated through the BMS.

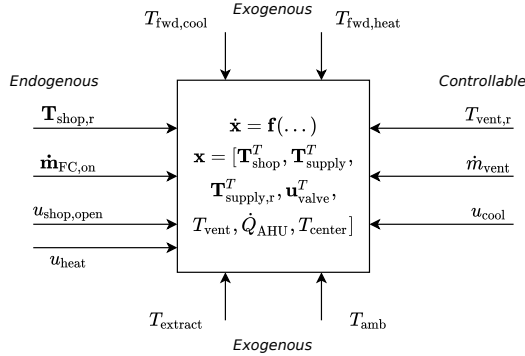


Fig. 4.3: Diagram depicting model states and inputs. Endogenous are the inputs that are driven by a schedule. The exogenous inputs are external and not controllable. This is in the context of the BMS in Kolding Storcenter.

4.2.1 Identification of model parameters

Parameter estimation, especially for models of large buildings, is a very complex problem to solve. The method used for the majority of the works in this thesis has to a large extent been based on table-lookup and manual flow measurements to determine steady-state heat flows. The most difficult parameters to estimate have been thermal capacities and thermal resistances. Closing down shops for parameter estimation experiments is not a feasible solution. This leaves a closed-loop parameter estimation problem with multiple uncertainties.

In **Table 4.1** parameters are shown (for a single shop) and **Figure 4.4** shows a comparison between model and measurements. The comparison is based on consecutive data of 30 days from mid-September to mid-October (2019). The results shown in **Figure 4.4** are quite promising, with a Root-Mean-Square Error (RMSE) for the shop temperature of 0.46 K. Especially also considering how well the model captures the PI controller states; $T_{\text{supply},r,i}$ and the valve openings. The valve openings do not feature great RMSE values, but qualitatively the model captures whether the system is trying to heat or cool and to a great extent also the magnitude. Notice however that the cooling valve opening saturates, which is not desirable, and reveals capacity issues or misconfiguration.

More fitting results are presented in **Paper A**, **Paper C** and **Paper D** in particular.

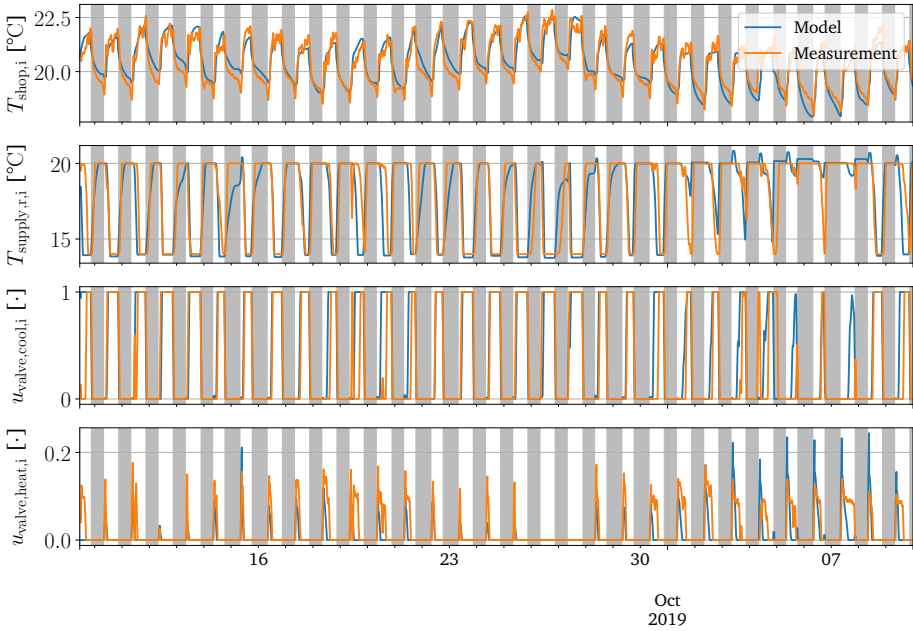


Fig. 4.4: Comparing simulation of Kolding Storcenter to measurement data. The following goodness-of-fit (RMSE) measures were obtained; T_{shop} : 0.46 K, T_{supply} : 0.70 K, $u_{\text{valve,cool}}$: 0.32, $u_{\text{valve,heat}}$: 0.04.

4.3. Decentralized AHUs and central cooling

Table 4.1: Kolding Storcenter model parameters (single shop)

Area	C_{shop}	$C_{\text{AHU},0,i}$	\dot{Q}_{int}	$R_{\text{shop-amb}}$	$R_{\text{AHU},0,i-\text{amb}}$
250 m ²	5.0 MJ/K	2.0 MJ/K	5.0 kW	0.001 K/W	0.001 K/W
α_{cool}	α_{heat}	$K_{p,\text{shop}}$	$K_{i,\text{shop}}$	$K_{p,\text{supply}}$	$K_{i,\text{supply}}$
0.03 kg/s	0.2 kg/s	5	0.0025	0.5	0.02
$C_{\text{AHU},0}$	$R_{\text{AHU},0,i-\text{amb}}$	$K_{p,\text{AHU},0}$	$K_{i,\text{AHU},0}$	k_i	$T_{\text{fwd},\text{hot}}$
2.0 MJ/K	0.001 K/W	30	0.2	0.2	55 °C
τ_{extract}			τ_{extract}		
1 h			10 h		

4.3 Decentralized AHUs and central cooling

Another example of a shopping center HVAC system is CITY2, which features ventilation through decentralized AHUs and cooling through one central cooling plant. A model of the HVAC system is presented in **Paper E**, which captures the main dynamics of the AHUs in the SEBUT demo-zone. This section summarizes the work.

The model relates to the HVAC diagram depicted in **Figure 4.5**.

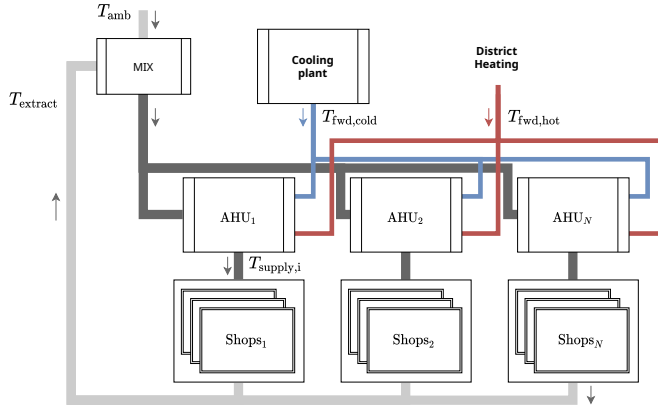


Fig. 4.5: HVAC layout in CITY2. Decentralized AHUs sharing mixing chambers. Central cooling plant delivering cooling to all AHUs.

The supply temperature dynamics for the i -th AHU are modeled as:

$$C_{\text{AHU},i} T_{\text{supply},i} = \dot{Q}_{\text{cool},i} + \dot{Q}_{\text{heat},i} + \dot{Q}_{\text{AHU-amb},i} - \dot{Q}_{\text{AHU},i} \quad (4.25)$$

where $C_{\text{AHU},i}$ is a lumped thermal capacitance for the AHU, $\dot{Q}_{\text{cool},i}$ and $\dot{Q}_{\text{heat},i}$ are heat flows from cooling and heating coils to the supply air, $\dot{Q}_{\text{AHU-amb},i}$

is heat loss to the ambient (the mixing chamber) and $\dot{Q}_{\text{AHU},i}$ is the heat flow supplied to the shops.

The heat flows from cooling and heating coils are given by:

$$\dot{Q}_{\text{cool},i} = u_{\text{cool}} \alpha_{\text{cool},i} u_{\text{valve,cool},i} c_{p,\text{water}} (T_{\text{fwd,cool}} - T_{\text{supply},i}) \quad (4.26)$$

$$\dot{Q}_{\text{heat},i} = u_{\text{heat}} \alpha_{\text{heat},i} u_{\text{valve,heat},i} c_{p,\text{water}} (T_{\text{fwd,heat}} - T_{\text{supply},i}) \quad (4.27)$$

with u_{cool} and u_{heat} indicating whether cooling and heating is ON (1) or OFF (0). The parameters, $\alpha_{\text{cool},i}$ and $\alpha_{\text{heat},i}$, cover both coil efficiency and valve characteristics. The valve opening degrees are given by $u_{\text{valve,cool},i}$ and $u_{\text{valve,heat},i}$. Forward temperature from the cooling plant is given by $T_{\text{fwd,cool}}$ and forward temperature from district heating is given by $T_{\text{fwd,heat}}$.

As noted in **Section 2.2**, the AHUs are grouped together and share the same mixing chamber – which they are placed inside. The heat loss from AHU to the surroundings is therefor the loss to the mixing chamber:

$$\dot{Q}_{\text{AHU-amb},i} = \frac{1}{R_{\text{AHU-amb},i}} (T_{\text{mix}} - T_{\text{supply},i}) \quad (4.28)$$

where $R_{\text{AHU-amb},i}$ is the thermal resistance and T_{mix} is the temperature of the mixing chamber. The heat flow supplied to the shops is given by:

$$\dot{Q}_{\text{AHU},i} = \dot{m}_{\text{AHU},i} c_{p,\text{air}} (T_{\text{mix}} - T_{\text{supply},i}) \quad (4.29)$$

$$\dot{m}_{\text{AHU},i} = u_{\text{AHU},i} \bar{\dot{m}}_{\text{AHU},i} \quad (4.30)$$

where $u_{\text{AHU},i}$ determines whether the AHU is ON (1) or OFF (0) and $\bar{\dot{m}}_{\text{AHU},i}$ is a constant flow parameter, as the AHUs are operated in a CAV manner.

As noted in **Section 2.2**, the AHUs rely on supply air temperature control. This controller then manipulate with the valve openings. This controller is modeled as a PI controller:

$$\dot{u}_{\text{valve},i} = -K_{p,i} \dot{T}_{\text{supply},i} + K_{i,i} (T_{\text{supply},r,i} - T_{\text{supply},i}) \quad (4.31)$$

$$u_{\text{valve,cool},i} = \max\{-u_{\text{valve},i}, 0\} \quad (4.32)$$

$$u_{\text{valve,heat},i} = \max\{u_{\text{valve},i}, 0\} \quad (4.33)$$

where $u_{\text{valve},i}$ is a combined valve opening signal covering both cooling (negative for open) and heating valve (positive for open). Controller proportional gain is K_p and integral gain is K_i .

The model is summarized in **Figure 4.6**, showing the classification of the above model variables in states and inputs. The classification of controllable inputs is in the context of CITY2 – knowing what can be manipulated through the BMS.

4.3. Decentralized AHUs and central cooling

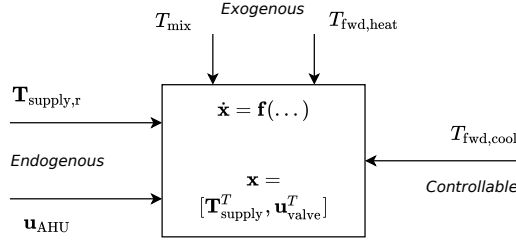


Fig. 4.6: Diagram depicting model states and inputs. Endogenous are the inputs that are driven by a schedule. The exogenous inputs are external and not controllable. This is in the context of the BMS in CITY2.

4.3.1 Identification of model parameters

Model parameters have been identified in a similar way as described in **Section 4.2.1**, using table-lookup and the known specifications for the AHUs. In **Table 4.2** parameters are shown (for a single AHU) and **Figure 4.7** shows a comparison between model and measurements. The comparison is based on consecutive data of 26 days from mid-July to mid-August (2020). Looking at **Figure 4.7**, the majority of the important dynamics of the supply temperature and also to a large degree the behavior of the controller is captured. A RMSE of 1.55 K is obtained for the supply temperature, which is worse than the fit on temperature dynamics in Kolding Storcenter. The fit is especially not good when the AHUs are OFF. A remedy to this has not been found, as the behaviour of the supply temperature when OFF is not reflected in any of the signals exposed by the BMS. However, since control authority is limited to when the AHUs are ON, this is a non-issue for a control-oriented model.

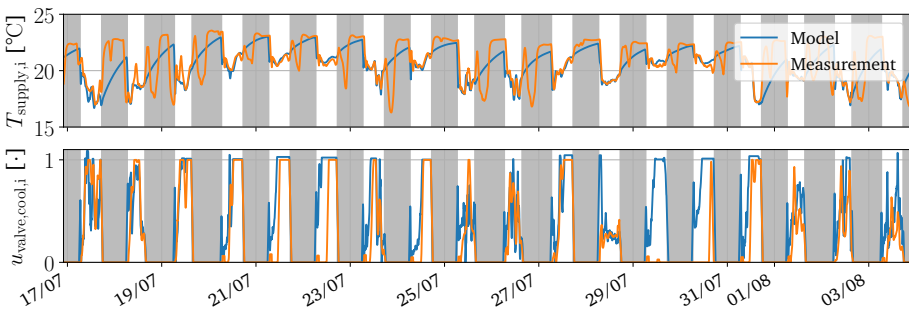


Fig. 4.7: Comparing simulation of CITY2 to measurement data. The following goodness-of-fit (RMSE) measures were obtained; T_{supply} : 1.55 K, $u_{\text{valve,cool}}$: 0.26.

Chapter 4. Modeling shopping center temperature dynamics

Table 4.2: CITY2 model parameters (single AHU)

$C_{\text{AHU},i}$	$R_{\text{amb-AHU},i}$	α_{cool}	α_{heat}	$K_{p,i}$	$K_{i,i}$	$\dot{m}_{\text{AHU},i}$
40.0 MJ/K	0.001 K/W	12 kg/s	- kg/s	0.5	0.001	12 kg/s

5 | Energy-efficient control

This chapter summarizes the work in developing energy-efficient control algorithms for shopping center HVAC. The primary objective is to maintain or improve thermal comfort in the shops while improving energy-efficiency of the HVAC system. While general occupant comfort is not limited to temperature, it was found to be the most dominating factor for the level of ventilation in the SEBUT project[64].

As indicated in **Section 1.2**, state-of-the-art within building control is MPC. The application of MPC to shopping centers has been a big focus area for this thesis, as the promises set forth are not to be neglected – the method is all-encompassing to the control problems in this project. The first part of this chapter will treat MPC within the goal of energy-efficiency.

There are drawbacks to MPC, however. These were pointed out in **Section 1.2** and have also been encountered in this project: the dependency on an accurate dynamical model of the system. In a retrofit situation, this dependency can potentially hinder the application of MPC. By investigating the benefits and the behavior of using MPC in terms of energy-efficiency, which were first pointed out in **Paper C**, it was concluded that a similar response could be achieved using something *less complex*. This led to the first steps to a new control architecture as an alternative and less-involved approach to MPC. **Paper D** presents these steps together with a comparison to MPC. In continuation, **Paper E** presents experimental results from using the proposed architecture in Kolding Storcenter and **Paper F** further generalizes and enhances the method, applies it to two case studies and presents comparison results to MPC for both case studies. The second part of this chapter presents the final version of this new control architecture.

5.1 Model Predictive Control

The goal of designing a stabilizing feedback which also minimizes a performance criteria while not violating given constraints is common between many control problems. Closed solutions to these problems are often not ob-

tainable[65]. One approach is instead to formulate an open-loop finite horizon optimal control problem and solve it in a receding horizon fashion. This is popularized as MPC. Summarized, at each sample instant, k , the following steps are undertaken:

1. Obtain state, $\mathbf{x}(k)$ (or state estimate)
2. Solve optimal control problem (initial state = $\mathbf{x}(k)$), yielding control \mathbf{u}
3. Apply control input $\mathbf{u}(k)$ (or part of \mathbf{u})
4. *Repeat*

Letting $\mathbf{x} \in \mathbb{R}^{n_x}$ denote the state, $\mathbf{u} \in \mathbb{R}^{n_u}$ the control input, $\mathbf{u}_{\text{ex}} \in \mathbb{R}^{n_e}$ the disturbances and $\mathbf{y} \in \mathbb{R}^{n_y}$ the output, a general continuous-time optimal control problem can be formulated as:

$$\min_{\mathbf{u}} J = \int_{t_0}^{t_f} g(\mathbf{x}, \mathbf{u}, \mathbf{u}_{\text{ex}}, \mathbf{y}) \, dt \quad (5.1)$$

subject to:

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{u}_{\text{ex}}(t)) & (\text{dynamics}) \\ \mathbf{y} &= \mathbf{h}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{u}_{\text{ex}}(t)) & (\text{output}) \end{aligned}$$

and subject to e.g. state, input and output box constraints:

$$\begin{aligned} \mathbf{x}_{\min} &\leq \mathbf{x} \leq \mathbf{x}_{\max} \\ \mathbf{u}_{\min} &\leq \mathbf{u} \leq \mathbf{u}_{\max} \\ \mathbf{y}_{\min} &\leq \mathbf{y} \leq \mathbf{y}_{\max} \end{aligned} \quad (5.2)$$

with \leq taken element-wise.

The objective function, g , maps states, inputs and outputs to \mathbb{R} . System dynamics are given by \mathbf{f} , not limiting the formulation to linear systems. Only box constraints are shown in Eq. (5.2), but constraints on boundary conditions can also be posed, e.g. on final time (t_f), value of state or output at final time.

If the objective function, g , is linear or quadratic and if the constraints are all linear (including the system dynamics), a solution is obtainable using either Linear Programming (LP) or Quadratic Programming (QP) – if it exists. Using either LP or QP, the benefit is guaranteed efficient global solutions using a myriad of available solvers. If not imposing this restriction, a solution is obtainable using Nonlinear Programming (NLP). While this ensures that no model information is lost in a potential linearization of the system dynamics, it does not guarantee global solutions and has significant higher computational complexity. However, the popularization of tools such as acados[66], ICLOCS[67] and CasADi[62] has made nonlinear optimal control significantly more accessible for all kinds of control problems.

All these tools take the same approach to solving nonlinear optimal control problems such as Eq. (5.1). First the infinite dimensional (continuous-time) problem is *transcribed*: the problem is discretized to a finite dimensional NLP. The most common methods for transcription are either multiple-shooting or direct collocation. The NLP can then be solved using available solvers, e.g. IPOPT[68].

In this project, CasADi has been used extensively. This allows posing the model dynamics once and using that formulation for both simulations and to pose and solve optimal control problems subject to those dynamics. The go-to method has been multiple-shooting using a standard *4th-order Runge-Kutta* integrator.

5.1.1 Energy-efficient cooling in Kolding Storcenter

In **Paper C**, MPC is employed to reduce cooling consumption in the heating season in Kolding Storcenter. As indicated in **Section 2.1**, there is a very large cooling consumption in Kolding Storcenter, which originates from large heat gains in shops. In **Figure 5.1**, this cooling consumption is visualized by showing BMS data from three days in December 2018. The data reveals both a heating and cooling demand from the three shops investigated. Furthermore, the data reveals that the associated AHU heats the supply air ($T_{\text{vent}} > T_{\text{amb}}$) while the also associated chiller is also operational (seen by low and oscillating $T_{\text{fwd,cool}}$) – thus both heating and cooling at the same time. This is not desirable. One approach to minimizing the cooling consumption, would be to simply not allow the chiller to turn on. Given the HVAC as described in **Section 2.1**, this would lead to a loss in control authority in the shops. The necessary coordination to avoid heating and cooling at the same time, is achievable with MPC, which is demonstrated through simulations. The MPC is designed by formulating a nonlinear optimal control problem as Eq. (5.1), where the objective function is the combined cooling effort by both AHU and chiller:

$$\dot{Q}_{\text{cool,tot}} = \sum_{i=1}^{N_{\text{shops}}} \dot{Q}_{\text{AHU},i}^- + \dot{Q}_{\text{cool},i} \quad (5.3)$$

where $\dot{Q}_{\text{AHU},i}$ and $\dot{Q}_{\text{cool},i}$ are presented in **Section 4.2** and $\dot{Q}_{\text{AHU},i}^-$ is only the negative part of $\dot{Q}_{\text{AHU},i}$ (only cooling). The optimal problem considered:

$$\min_{\mathbf{u}} J = \int_{t_0}^{t_f} \dot{Q}_{\text{cool,tot}}^2 dt \quad (5.4)$$

subject to similar nonlinear dynamics as presented in **Section 4.2**.

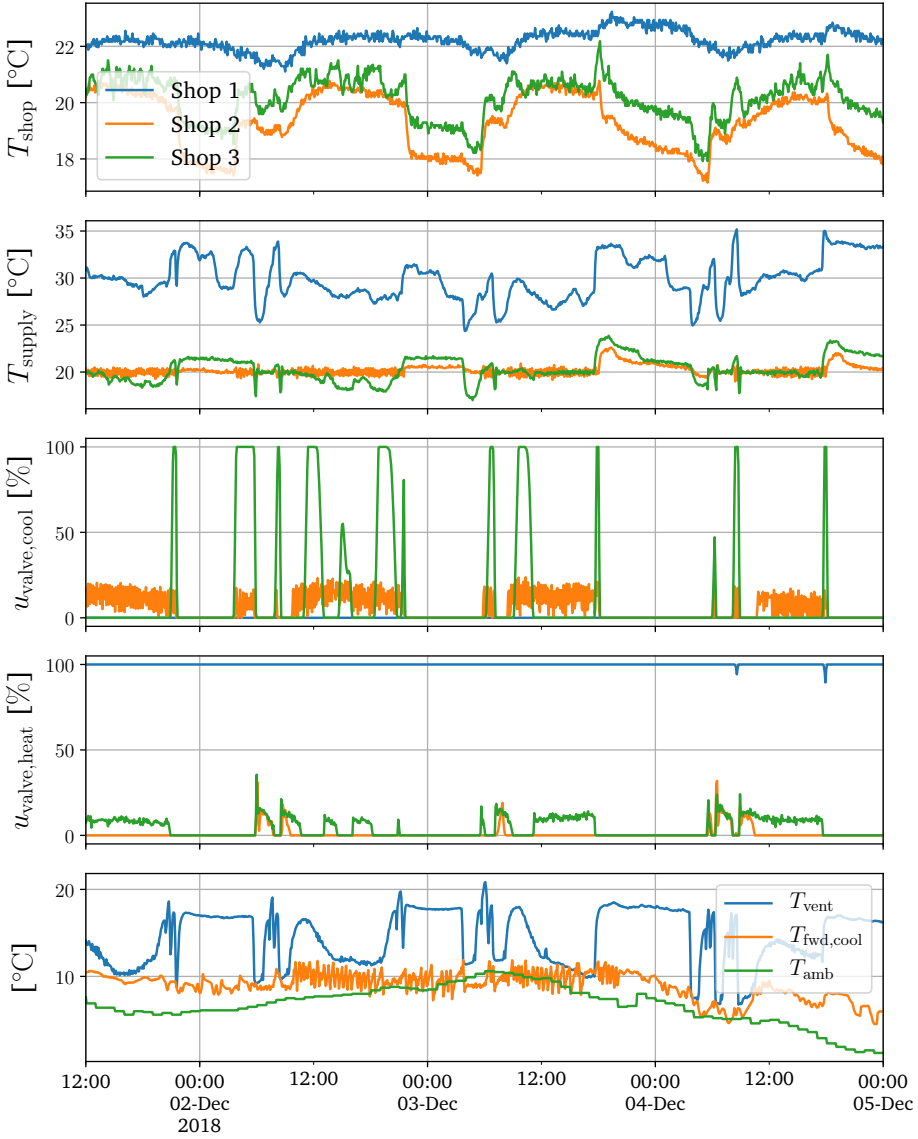


Fig. 5.1: Measurement data extracted from BMS in Kolding Storcenter. The three shops shown behave differently; Shop 1 features large heating demand (heating valve saturating at 100 % all the time). Shop 2 and Shop 3 features both cooling and heating demand. The AHU uses heating sometimes, as indicated by $T_{\text{vent}} > T_{\text{amb}}$ during operational hours[69]. © 2019 IEEE

The control inputs considered are supply air temperature from AHU (set-point), $T_{\text{vent},r}$, and the forward temperature for the chiller (setpoint), $T_{\text{fwd,cool},r}$. Suitable constraints were enforced on both shop temperatures, supply temperatures and forward temperature. All states in the model are measurable

5.1. Model Predictive Control

(a direct consequence of formulating the model based on the available measurements) and so no state estimation is required. No prediction model of the disturbances was used – instead, the fact that the system is close to being periodic is used, by applying yesterday’s inputs delayed 24 h for prediction. The control diagram is depicted in **Figure 5.2**.

Using this MPC, it was possible to shift cooling capacity from the chiller to the AHU instead. Eliminating the need to use the chiller in the simulation results and instead driving the AHU with a lower supply air temperature – this is more reasonable, as passive cooling is available through the low ambient temperature. Results showing the lowered cooling effort are presented in **Figure 5.3**. Total energy savings during the simulation were 21 %. This was calculated taking into account additional heating in the FCUs, as a lower supply temperature of the air from the AHU would potentially have the FCU supply temperature control open the heating valves more.

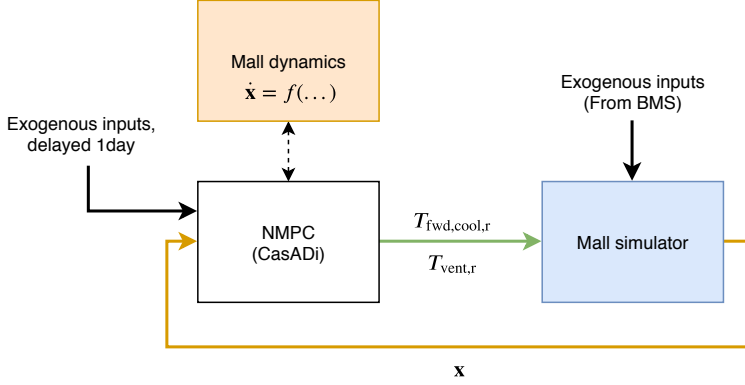


Fig. 5.2: Diagram depicting MPC simulation setup as studied in **Paper C**.

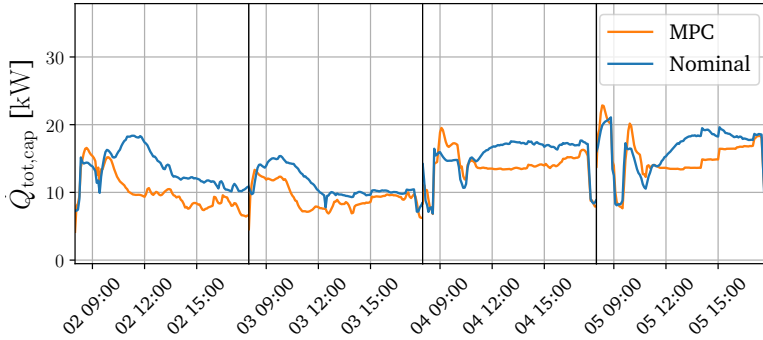


Fig. 5.3: Simulation result showing how MPC lowers the total cooling effort by not heating supply air in the AHU and not using the chiller[69]. © 2019 IEEE

5.1.2 Energy-efficient cooling in CITY2

In **Paper F**, MPC is employed to reduce cooling consumption during summer in CITY2. As described in **Section 2.2**, the cooling consumption is significantly lower than Kolding Storcenter and is limited to May, June, July and August. The MPC draws on results from a preliminary control design presented in **Paper A**, which introduces feedback on the cooling valve opening signals and manipulates forward temperature to drive the most open valve towards fully open. A higher forward temperature is desirable to increase the Coefficient of Performance (COP) of the system. The theoretical COP limit is determined by the COP of a Carnot cycle¹:

$$\text{COP}_{\max} = \frac{T_{\text{fwd,cool}}}{T_{\text{amb}} - T_{\text{fwd,cool}}} \quad (5.5)$$

This means that efficiency increases when driving the forward temperature closer to the ambient temperature. With feedback on valve openings, the forward temperature can be increased while ensuring that demand is still met, by not allowing the valves to saturate completely. In **Paper A** this is done using a PI controller:

$$e = u_{\text{valve,cool,r}} - \max(\mathbf{u}_{\text{valve,cool}}) \quad (5.6)$$

$$T_{\text{fwd,cool,r}} = K_p e + K_i \int e \, dt \quad (5.7)$$

where $u_{\text{valve,cool,r}}$ could be selected as 90 % open, to allow for a saturation margin. In **Paper F** the same principle is realized using MPC, by considering the following optimal control problem:

$$\min_{\mathbf{u}} J = \int_{t_0}^{t_f} q_e \mathbf{e}_{\text{supply}}^T \mathbf{e}_{\text{supply}} + (u_{\text{valve,cool,r}} - \max(\mathbf{u}_{\text{valve,cool}}))^2 \, dt \quad (5.8)$$

where $\mathbf{e}_{\text{supply}}$ is the vector of error signals from the AHU supply temperature control which is modeled in **Section 4.3**. The objective both considers minimizing controller error (thermal comfort) and driving valve opening towards $u_{\text{valve,cool,r}}$. The benefit of using MPC in this setting lies in both the ability to handle constraints and in predictions, which allows for foresightedly lowering $T_{\text{fwd,cool}}$ for peak cooling demand. However, the cost is still the requirement of a dynamical model – which makes the PI controller version very attractive.

In **Paper F** the MPC is compared to a nominal control situation, where the forward temperature is controlled through a setpoint curve, which is very common practice and what is already implemented in CITY2. Simulations of all the summer months are conducted and it is estimated that energy

¹This expression is only valid for cooling in summer, where T_{amb} is higher than what is being cooled.

savings of 11 % are achievable when comparing to the nominal controller. In the SEBUT project[64], it is estimated that the energy consumption of the cooling plant in CITY2 can be reduced with 3 % for every degree the forward temperature is increased. This is on par with the results of the simulation.

5.2 Low-complexity Hierarchical Control

HVAC systems can be divided into *consumers* and *producers*, and as has also been identified through the SEBUT project, many control related issues lie in the coordination between these two groups. In HVAC systems, it can be natural to characterize thermal zones as the consumers – for shopping centers, the shops. In the following, a *consumer* has to have a temperature controller, which will regulate how much heating/cooling of the HVAC system capacity is used. A *producer* delivers heating/cooling capacity, determined by an actuator that can be manipulated.

To balance production and demand of the consumers, a hierarchical control approach is proposed and presented in **Figure 5.4**.

Letting \dot{Q}_{demand} be the total heat demand² of all consumers and $\dot{Q}_{\text{produced}}$ the heat delivered to the consumers by the producers, the following energy balance is considered:

$$\dot{Q}_{\text{demand}} = \dot{Q}_{\text{produced}} + \Delta\dot{Q}_{\text{demand}} \quad (5.9)$$

The desire is to control $\dot{Q}_{\text{produced}}$ to match \dot{Q}_{demand} ; in this situation the consumers have *just enough* heating/cooling capacity to meet their demand. When they do not match, a discrepancy, $\Delta\dot{Q}_{\text{demand}}$, appears:

$$\Delta\dot{Q}_{\text{demand}} = \sum_i^N \Delta\dot{Q}_{\text{demand}} = \dot{Q}_{\text{demand}} - \dot{Q}_{\text{produced}} \quad (5.10)$$

The control problem of balancing production and consumption can therefor be re-stated as a desire to have $\Delta\dot{Q}_{\text{demand}}$ go to zero. Assuming $\Delta\dot{Q}_{\text{demand}}$ unknown, \dot{Q}_{demand} known and $\dot{Q}_{\text{produced}}$ controllable through the reference, $\dot{Q}_{\text{produced},r}$, the control problem can be solved by letting:

$$\dot{Q}_{\text{produced},r} = \dot{Q}_{\text{produced}} + \Delta\dot{Q}_{\text{demand}} \quad (5.11)$$

²Heating (positive) or cooling (negative).

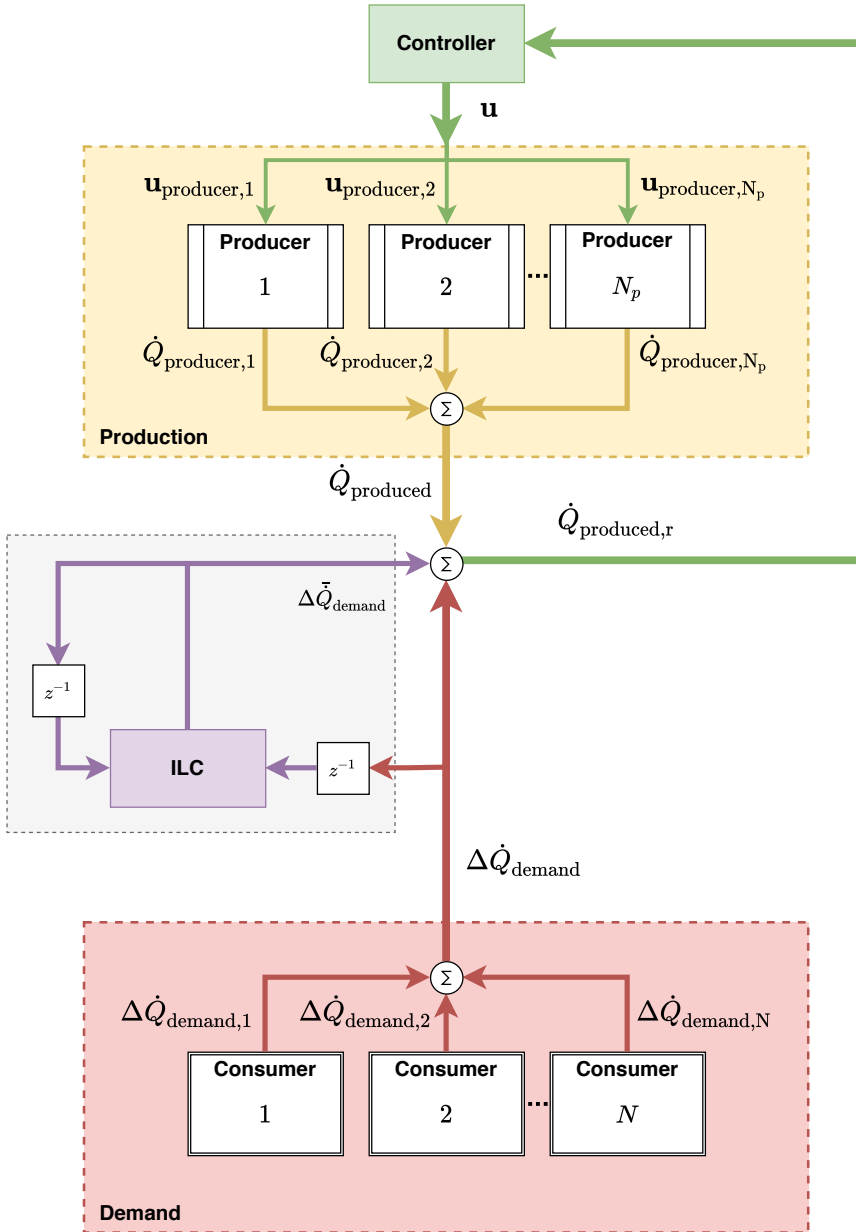


Fig. 5.4: The final generalized hierarchical control approach as it is presented in **Paper F** – developed through **Paper D**, **Paper E** and **Paper F**. [70]

5.2. Low-complexity Hierarchical Control

With the further assumptions of no dynamics in the producers and perfect tracking of this reference, one has:

$$\dot{Q}_{\text{produced},r}(t) = \int_{t_0}^{t_f} \Delta \dot{Q}_{\text{demand}}(t) dt + \dot{Q}_{\text{produced}}(t_0) \quad (5.12)$$

Since $\Delta \dot{Q}_{\text{demand}}$ can be considered the error and $\dot{Q}_{\text{produced},r}$ the control input, this is a pure integral controller, which will drive $\dot{Q}_{\text{produced},r}$ (and hence $\dot{Q}_{\text{produced}}$) to a point where $\Delta \dot{Q}_{\text{demand}}$ is zero – as long as the system does not saturate.

The method requires knowing $\Delta \dot{Q}_{\text{demand}}$. Here, an estimate, $\Delta \hat{Q}_{\text{demand}}$, is proposed:

$$\Delta \hat{Q}_{\text{demand}} = \sum_i^N \Delta \hat{Q}_{\text{demand},i} \quad (5.13)$$

$$\Delta \hat{Q}_{\text{demand},i} = \dot{m}_{\text{nom},i} c_p e_i \quad (5.14)$$

This estimated is based on knowing nominal flow, $\dot{m}_{\text{nom},i}$, and the error signal, e_i , of the temperature regulator in the consumers – these are assumed obtainable in most HVAC systems. The estimate has a drawback, as it aggregates the individual demand terms using a summation. As the demand terms can be both positive and negative, this means that they can cancel each other out. With $N/2$ consumers demanding extra heating and $N/2$ consumers demanding extra cooling, it would lead to $\Delta \hat{Q}_{\text{demand}} = 0$. It is possible to treat heating and cooling separately to handle mixed-mode situations, but this would be at a cost of total system efficiency – allowing both heating and cooling at the same time.

Now, knowing what $\dot{Q}_{\text{produced},r}$ to use, another control problem arises in tracking this reference and dividing the load among the producers. This is the job of the block marked *Controller* in **Figure 5.4**. Let \mathbf{u} be the control input to all the producers:

$$\mathbf{u} = [\mathbf{u}_{\text{producer},1}, \mathbf{u}_{\text{producer},2}, \dots, \mathbf{u}_{\text{producer},N_p}]^T \quad (5.15)$$

and let \mathbf{y} denote the vector of available measurements. It is assumed that a static model, $\dot{Q}_{\text{produced}}(\mathbf{u}, \mathbf{y}) \in \mathbb{R}$, of the produced heat is known. It is also assumed that a static model, $\kappa(\mathbf{u}, \mathbf{y})$, of cost of $\dot{Q}_{\text{produced}}$ is known. Here cost can be e.g. monetary cost or power consumption. The following optimization problem is posed:

$$\min_{\mathbf{u}} J = q_d \left(\dot{Q}_{\text{produced},r} - \dot{Q}_{\text{produced}}(\mathbf{u}, \mathbf{y}) \right)^2 + q_c \kappa(\mathbf{u}, \mathbf{y}) \quad (5.16)$$

subject to:

$$\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max}$$

Here q_d and q_c are tunable weights and \leq is taken element-wise. Solving this problem finds the producer control inputs that balances production with consumption while minimizing the cost of using those control inputs.

This problem is a steady-state optimization problem that only requires static models of the heat produced and the cost of producing it. Impact-wise this is important, as this method does not rely on an accurate dynamical model as is the case for MPC. Furthermore, a steady-state optimization problem can potentially be sampled in a grid and converted to a look-up table. This is an important trait when considering commissioning.

The final addition, as was introduced in **Paper F**, is ILC. The prospect of exploiting inherent periodic behavior in the examined HVAC systems was first treated in **Paper D**, but the periodic behavior was first quantified in **Paper F**. A frequency analysis (Fast Fourier Transform (FFT)) on error signals from shop temperature controllers in Kolding Storcenter made a 1-day periodicity very clear. The frequency analysis is shown in **Figure 5.5**. Besides the 1-day periodic behavior, **Figure 5.5** also shows some weekly periodicity, which is in line with different opening hours and HVAC operation schedule during the weekend.

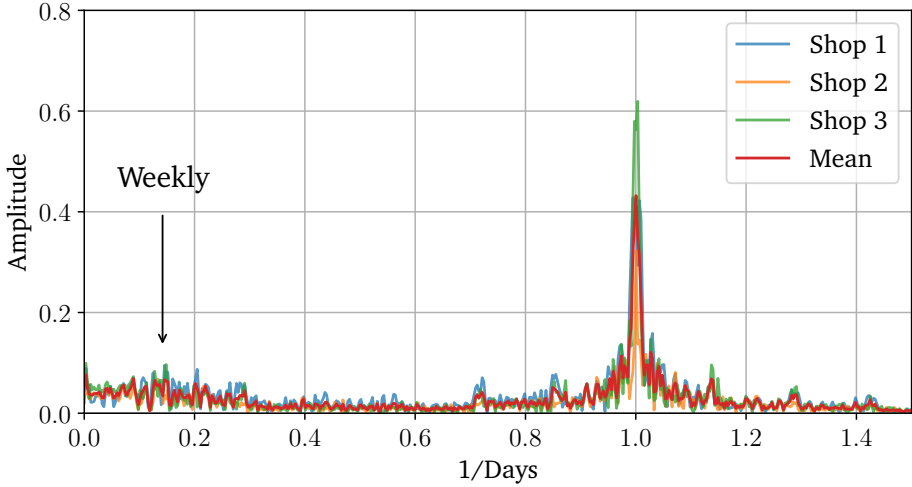


Fig. 5.5: Frequency analysis (FFT) of shop temperature controller error signals, e_i . For three shops in Kolding Storcenter. Data used is hourly data from August 2019 to August 2020.[71]

The addition of ILC is also depicted in **Figure 5.4**, where it sits in parallel to the aggregated demand, $\Delta\dot{Q}_{\text{demand}}$. Considering the discrete-time version of Eq. (5.11) and adding the ILC contribution:

$$\dot{Q}_{\text{produced},r,j}(k) = \dot{Q}_{\text{produced},j}(k) + \Delta\dot{Q}_{\text{demand},j}(k) + \Delta\dot{Q}_{\text{ILC},j}(k) \quad (5.17)$$

where j is the trial index (or iteration index) and k is the time index (or sample

5.2. Low-complexity Hierarchical Control

index). The ILC contribution, $\Delta\dot{Q}_{\text{ILC},j}(k)$, is calculated according to a simple proportional ILC update law:

$$\Delta\dot{Q}_{\text{ILC},j+1}^*(k) = \alpha\Delta\dot{Q}_{\text{ILC},j}(k) + L \Delta\dot{Q}_{\text{demand},j}(k+1) \quad (5.18)$$

where α is a forgetting factor ($0 < \alpha \leq 1$) and L is the ILC learning gain. The forgetting factor is used to ensure stability of $\Delta\dot{Q}_{\text{ILC},j}(k)$ when considering seasonal effects. One example; going from cold weather to warm weather back to cold. Going from cold weather to warm weather has the ILC learn a need for extra cooling capacity. Going from the warm weather to cold weather again does not necessarily unlearn the effect if the consumers are perfectly capable of maintaining the temperature with the added cooling capacity available but not used. This has to be unlearned again, hence the forgetting factor.

Furthermore, anti-windup is introduced by saturating the ILC contribution:

$$\Delta\dot{Q}_{\text{ILC},j+1}(k) = \begin{cases} \Delta\dot{Q}_{\text{ILC},\min}, & \text{for } \Delta\dot{Q}_{\text{ILC},j+1}^*(k) \leq \Delta\dot{Q}_{\text{ILC},\min} \\ \Delta\dot{Q}_{\text{ILC},\max}, & \text{for } \Delta\dot{Q}_{\text{ILC},j+1}^*(k) \geq \Delta\dot{Q}_{\text{ILC},\max} \\ \Delta\dot{Q}_{\text{ILC},j+1}^*(k), & \text{otherwise} \end{cases} \quad (5.19)$$

This is to avoid wind-up caused by capacity constraints, e.g. during peak weather conditions.

5.2.1 Experimental results from Kolding Storcenter

In **Paper E** the hierarchical approach, without ILC, is applied to the demo-zone in Kolding Storcenter. The desire is to minimize the cooling load, which exists even during winter as described in **Section 2.1**. The application considers controlling both the AHU and the chiller. The AHU by manipulating with supply air temperature (T_{vent}) and flow (\dot{m}_{vent}). The chiller by turning it ON/OFF.

Simple models for $\dot{Q}_{\text{produced}}$ (heating/cooling produced) are derived based on available flow and temperature measurements for both AHU and chiller. Cost, κ , is selected as power consumption, which is modeled by fitting polynomials to measurement data of power consumption and control inputs. The controller is implemented equivalent to **Figure 3.2**.

The controller was evaluated in the period from 9. November 2019 to 22. January 2020 – switching between the new controller and the baseline/nominal control for a fair comparison with similar ambient conditions. In **Figure 5.6** the results are summarized, with the new controller denoted *HCTRL* and the baseline/nominal controller denoted *Nominal*. The results

are very promising, showing on average 40 % savings for the chiller and on average 31 % for the AHU.

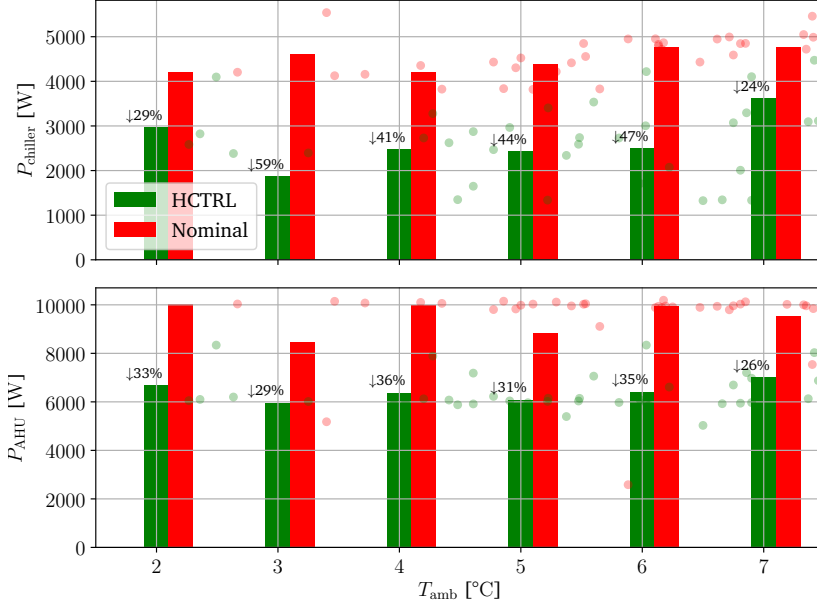


Fig. 5.6: Summarized energy savings from hierarchical control experiment in Kolding Storcenter[72].

5.2.2 ILC results

In **Paper F** the addition of ILC is evaluated in two case studies; both in Kolding Storcenter and CITY2. In both cases by comparing a simulation with and without the ILC. For Kolding Storcenter, the simulation is of five months, covering seasonal change (June to December). For CITY2 the simulation is three months (June, July, August). The metric compared on is an aggregated RMSE, averaged for each day in the simulation. The results for Kolding Storcenter are given in **Figure 5.7** and for CITY2 in **Figure 5.8**, where the RMSE is plotted against ambient temperature.

For Kolding Storcenter, the ILC provides on average 40 % reduction in the RMSE metric. The effect is higher for lower ambient temperatures, where there is more control authority – this is visible as RMSE is only kept close to zero until around $T_{amb} = 15^{\circ}\text{C}$. For higher ambient temperatures, it gets increasingly difficult to maintain the desired temperature.

In CITY2 there is plenty of control authority, with the very low RMSE. Only for ambient temperatures above 22°C the control struggles in the case of no ILC. When using ILC the performance is relatively constant over all

ambient temperatures considered.

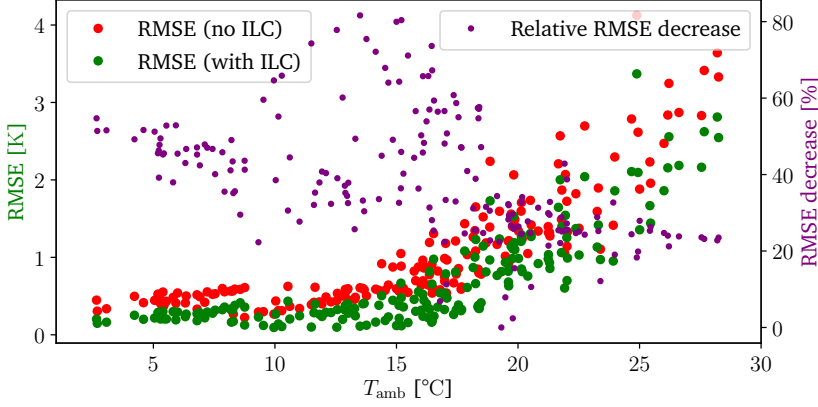


Fig. 5.7: Comparing simulation of using proposed hierarchical control approach, with and without ILC, in Kolding Storcenter[71].

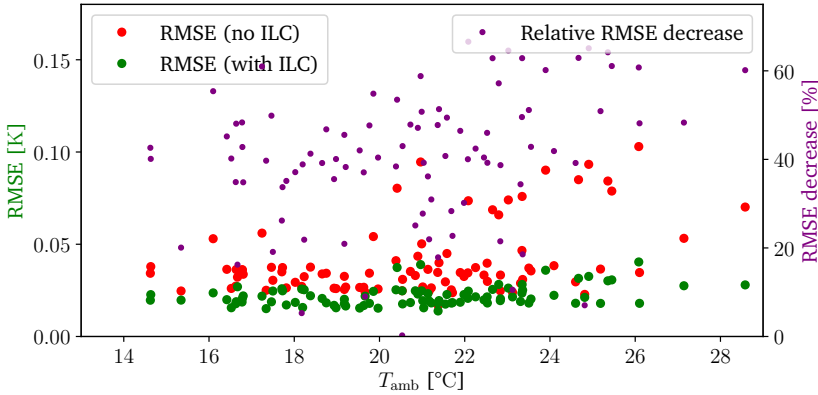


Fig. 5.8: Comparing simulation of using proposed hierarchical control approach, with and without ILC, in CITY2[71].

5.2.3 Comparison to MPC

In both **Paper D** and **Paper F** the proposed hierarchical control approach has been compared to MPC. Instead of attempting to do a realistic comparison between these methods, the MPC is treated as an upper-bound for achievable performance and has been provided ideal conditions; e.g. no model-mismatch (same nonlinear system dynamics in both simulation and MPC) and perfect prediction of exogenous disturbances.

The comparison for both Kolding Storcenter and CITY2 in **Paper F** shows

that the hierarchical control approach with ILC can recover up to 90 % of the equivalent MPC performance, while the transient response of control inputs can be significantly different. The comparison is on both thermal comfort and energy consumption and both controllers were evaluated for different sets of parameters (e.g. weights). The results are shown in **Figure 5.9** and **Figure 5.10**.

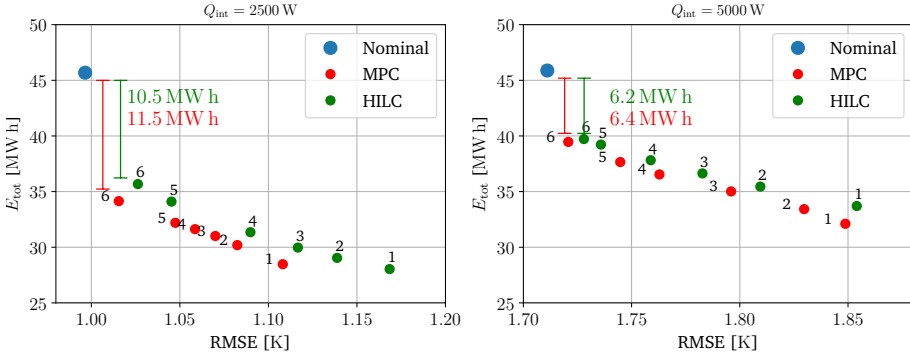


Fig. 5.9: Comparing simulation of using proposed hierarchical control approach (HILC) with ILC to MPC, in Kolding Storcenter[71].

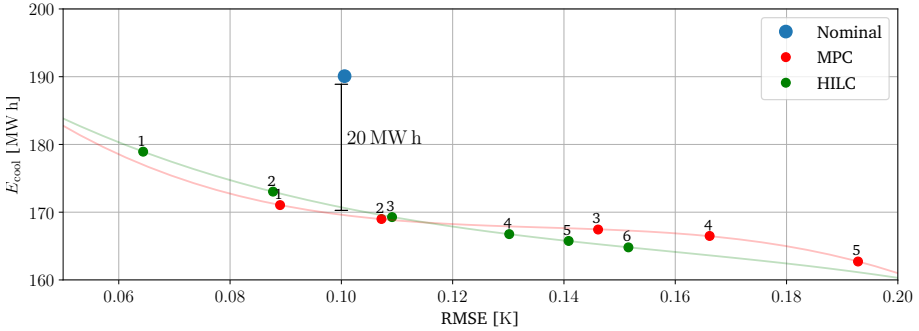


Fig. 5.10: Comparing simulation of using proposed hierarchical control approach (HILC) with ILC to MPC, in CITY2[71].

6 | Energy flexibility

This chapter summarizes the work within investigating the potential for energy flexibility in shopping centers. As presented in **Section 1.2.3**, energy flexibility in the domain of building control has many forms; indirect control through incentive signals (e.g. price) and direct control for deterministic power curtailment. Both indirect and direct control can provide peak-shaving and load-shifting. Besides this, energy flexibility can be both within electricity consumption and within heat consumption (district heating).

This chapter will seek to investigate the flexibility potential of shopping centers, through an investigation of the energy consumption in the two case studies; Kolding Storcenter and CITY2 – and through a simulation study in direct control as presented in **Paper B**.

6.1 Kolding Storcenter

As described in **Section 2.1**, Kolding Storcenter has a relatively high electricity consumption, given the large electricity consumption for cooling. Therefore, flexibility is investigated in terms of the electricity consumption. As Kolding Storcenter was outfitted with additional meters for power measurement in the SEBUT demo-zone, data collected here is used. Power measurements are collected for both the AHU and the chiller in the demo-zone; see **Figure 6.1**.

Of the total consumption in the demo-zone, the chiller is responsible for 36%. Note that this is not all the cooling. The AHU has, as described in **Section 2.1**, a built-in heat pump, making it able to cool the air. The effect of this is visible in **Figure 6.1** as roughly all AHU power consumption above 10 kW. Using power consumption models from **Paper E** and **Paper F**, the consumption can be split into what is cooling (28%) and what is ventilation (72%) for the AHU. That means, that cooling is 53% and ventilation is 47% of the total power consumption, for the demo-zone.

To investigate the potential for flexibility through indirect control, a correlation analysis is conducted. Calculating correlation between power con-

sumption and SPOT prices from the Danish electricity market on a daily basis (24h window). The consumption data from the COVID19 lock-down, visible in **Figure 6.1**, is removed, leaving a dataset of 8 months of data. The distribution of correlation coefficients calculated are given in **Figure 6.2**. Notice that data has been limited to hours between 06:00 and 23:55.

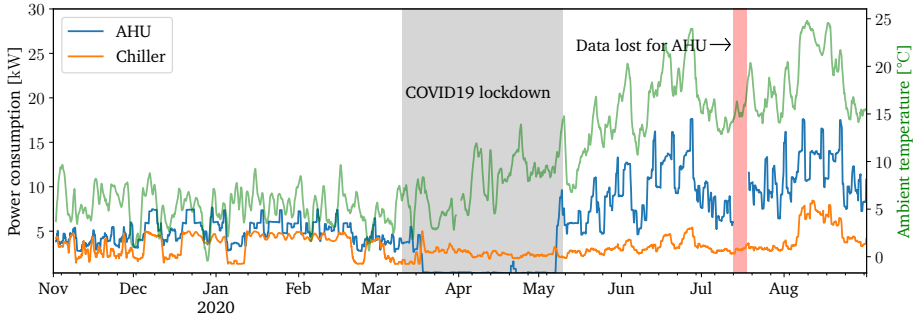


Fig. 6.1: Kolding Storcenter demo-zone power consumption (AHU and chiller), from Nov. 2019 to Sep. 2020 (daily average). Notice the 2 month long shut down due to COVID19.

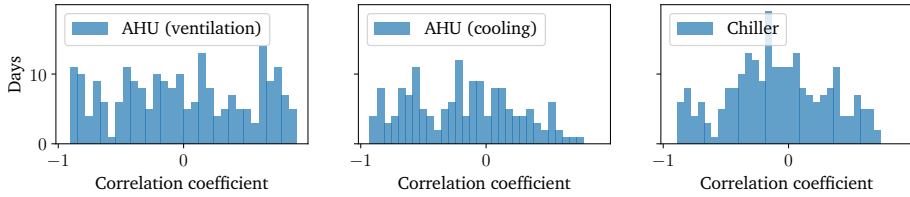


Fig. 6.2: Correlations coefficient between power consumption and SPOT prices of electricity (DK1), for (1) AHU (only ventilation/fans), (2) AHU (only cooling/heat pump), (3) chiller.

Looking at **Figure 6.2**, there is a clear potential to introduce indirect control using SPOT prices as incentive signal for especially ventilation and the chiller. As the ventilation is running constantly, at maximum capacity with measured low CO_2 levels in shops, there is a clear potential to introduce flow control including a SPOT price incentive signal. The same goes for the chiller. The correlation coefficients are also shown in **Figure 6.3**, as time series data. This reveals how the correlation shifts from heating season to cooling season. During the winter months there is a higher correlation with high SPOT prices, showing more potential.

Besides looking at the correlation between consumption and SPOT prices, the peak-shaving potential can be investigated by aggregating power consumption and SPOT price over the year and plotting an *average day*. The average day, considering power consumption spent on ventilation and the chiller (disregarding cooling in the AHU) is given in **Figure 6.4**. For the SPOT

price, this clearly identifies the two main peaks at 8:00 and at 19:00. There is a clear potential to reduce the load at the morning peak, as the AHU is started before 5:00 and reaches 8 kW ($\approx 80\%$ load) before 8:00. This is unnecessary given that shops do not open up until 10:00. Disregarding the chiller base load of 2 kW all day, the chiller's peak load as it starts in the morning is very close to the 8:00 peak, which also leaves potential for peak-shaving (or load-shifting).

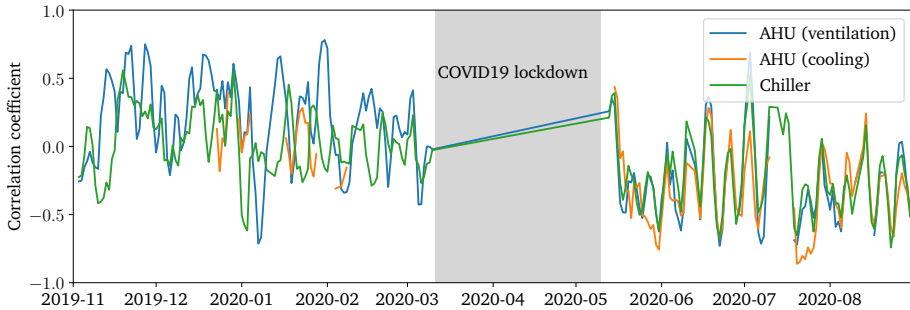


Fig. 6.3: Correlations coefficient between power consumption and SPOT price of electricity (DK1), for (1) AHU (only ventilation/fans), (2) AHU (only cooling/heat pump), (3) chiller. Time series, showing how the correlation changes.

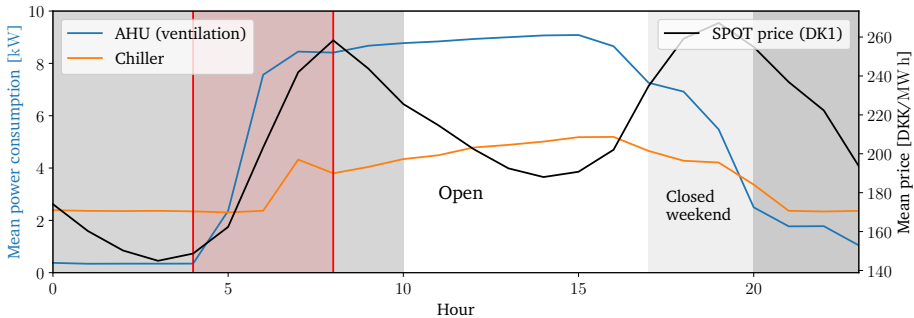


Fig. 6.4: Aggregated power consumption and SPOT price to visualize average day. Average SPOT price identifies the two peak loads of the electricity grid, at 8:00 and 19:00. Potential for load-shifting (or even reduction) is identified in the morning.

Another way to visualize the possibility of peak-shaving is through a Load Duration Curve (LDC), showing power consumption in descending order of magnitude instead of chronologically. An LDC is presented in **Figure 6.5** for both the AHU and the chiller. The potential for the AHU seems low given the LDC, in the sense that it does not exhibit a varying consumption with a strong peak that can be shifted. However, this is due to the fact that Kolding Storcenter operates the AHU in a CAV manner, and the potential

might be high if the AHU would instead be operated in a Variable Air Volume (VAV) manner, adjusting the flow to the demand of the shops.

For the chiller, the LDC indicates a strong peak. By low-pass filtering (cut-off frequency 1/4h) the power consumption data and producing the LDC again, the comparison between the two show, that the peak is not reduced, indicating that this large peak is in fact consecutive high consumption. Looking at **Figure 6.1** it is peak summer consumption, only happening in August where ambient temperatures reach 30 °C.

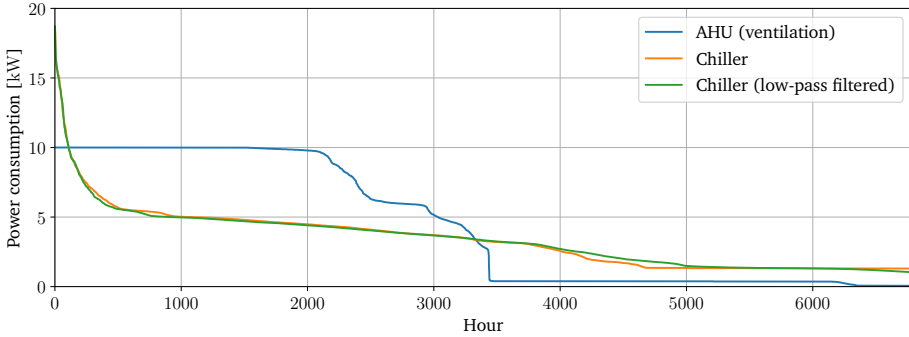


Fig. 6.5: Load Duration Curve for power consumption in Kolding Storcenter. For AHU (only ventilation) and for the chiller. For the chiller, the data is also low-pass filtered.

6.1.1 Load-shifting potential from exploiting thermal mass

While the previous analysis has been based in historical consumption data, this can not conclude on the load-shifting potential by exploiting thermal mass. This has been investigated in a deactivation experiment and through a simulation study using MPC in **Paper B**.

In the deactivation experiment, the power consumption of the AHU and chiller are directly manipulated for 1 h by introducing a step in air flow and by simply turning off the chiller entirely. The AHU air flow is reduced to 50 % of the nominal flow. The resulting shop temperatures and CO₂ level is shown in **Figure 6.6**. During this hour with limited air flow and the chiller not running, the shop temperature of *Shop 1* increases from $\approx 22^\circ\text{C}$ to 22.5°C while the temperature of *Shop 2* remains largely unchanged. The CO₂ level in Shop 2 increases slightly, from ≈ 465 ppm to ≈ 480 ppm. Given these small changes, it can be concluded that it is a non-issue to significantly reduce air flow and turn off cooling, in order to limit power consumption in a given hour. Lowering the air flow from the AHU by 50 % lowers the power consumption by 5 kW and turning off the chiller lowers the power consumption by 4 kW for a total 9 kW. Scaling this to the entire shopping center by number of AHUs and chillers provides for a total of 157 kW. The load-shifting

6.1. Kolding Storcenter

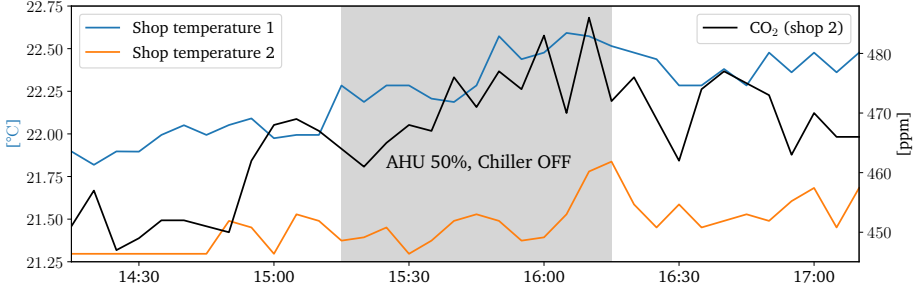


Fig. 6.6: Deactivation experiment in Kolding Storcenter, where the AHU air flow is reduced to 50% and the chiller is turned off, for 1 h during opening hours, to investigate potential for load-shifting. This experiment was conducted with an ambient of 10 °C.

potential was also evaluated in **Paper B**. In **Paper B**, the multi-zone dynamical model described in **Section 4.1** is used as the basis for a MPC design to introduce load-shifting through direct control of the power consumption, without violating thermal comfort constraints.

The direct control of power consumption is included in the MPC formulation as time-dependent constraints on the energy consumption:

$$\int_{t_{\text{on}}}^{t_{\text{off}}} P(t) \, dt = P_{\text{ref}}(t_{\text{off}} - t_{\text{on}}) \quad (6.1)$$

where P_{ref} is the desired consumption in the interval between t_{on} and t_{off} .

In **Paper B**, simulation studies on a model instantiated for Kolding Storcenter are conducted. The simulations considered the possibility of controlling chiller power consumption through manipulating with the forward temperature, $T_{\text{fwd,cool}}$ and by manipulating with the fan-coil supply temperature setpoints, $T_{\text{supply,r}}$. The power consumption model was based on modeled cooling capacity and a COP model from statistical data on heat pumps, as no power consumption data was collected for the chiller at this point.

The results from the simulation show a potential for load curtailment by restricting power (or energy) consumption in a specific interval through direct control – without violating thermal comfort constraints. The aggregated power curtailment for Kolding Storcenter is through this method estimated to be on the order of 100 kW for a period of 1 h – when only considering the chillers.

6.1.2 Unlocking the flexibility

Given the HVAC setup described for Kolding Storcenter in **Section 2.1** and **Section 4.2**, multiple ways of unlocking energy flexibility have been identified. These include:

- Turn off/on chiller(s) in given time slot
- Decrease/increase AHU(s) flow in given time slot
- Turn off/on fan coils units in given time slot
- Decrease/increase shop temperature setpoints in given time slot

Manipulating with individual fan coil units and shop temperature setpoints would allow for the highest level of granularity, and could allow for the shop owners to actively decide whether they would want to participate in flexibility aggregation and could potentially be rewarded for this. However it is the author's opinion, that while indeed possible, there are numerous lower hanging fruits ripe for plucking before such an elaborate demand-side flexibility scheme makes sense.

Manipulating with the operation of the chillers and the AHUs is the most feasible option, given the less intrusive control needed. For scale, this would still require interfacing with all chillers and all AHUs. The benefit of the decentralized HVAC is that it provides more granularity in the flexibility aggregation, e.g. not all chillers have to be turned on/off, thus not necessarily influencing the entire shopping center.

One way to introduce energy flexibility through control is achievable as an addition to the hierarchical control scheme described in **Section 5.2**. As the hierarchical control involves setpoint optimization through an optimization problem that can e.g. include the power consumption as cost, constraints could be introduced to limit power consumption in given hours. This would allow for direct control of the power consumption and could therefor market-wise be offered as regulating power sold on the Nordic regulating power market[46]. Evaluating this approach is future work.

6.2 CITY2

As described in **Section 2.2**, CITY2 has a very high heating consumption. Therefor, it is interesting to investigate the potentials for demand-side energy flexible heat consumption. While energy flexibility within district heating has not been as thoroughly treated in the literature as within electricity, it is still important given the desire to introduce renewables in the heat generation[73, 74, 75, 76]. One of the main benefits of demand-side flexibility in district heating systems is the possibility of peak-shaving. By peak-shaving it is possible for district heating suppliers to decrease the use of peak load plants and instead increase the load on base load plants. Reducing peak load can also set new lower requirements to dimensions in the district heating network.

In **Figure 6.7** the heat consumption from district heating in CITY2 for 2019 is shown together with the ambient temperature. In **Figure 6.8** the consumption is aggregated to show the median consumption over 24 h. From **Figure 6.8** it is possible to identify the morning peak at 8:00. This is undesirable from a district heating supplier point-of-view.

The peak-shaving potential is investigated in **Figure 6.9**, showing an LDC. In **Figure 6.9** a peak is identified and zooming in shows that for just 300 h ($\approx 3\%$ of the time) the consumption is above 2 MW, up to 3 MW.

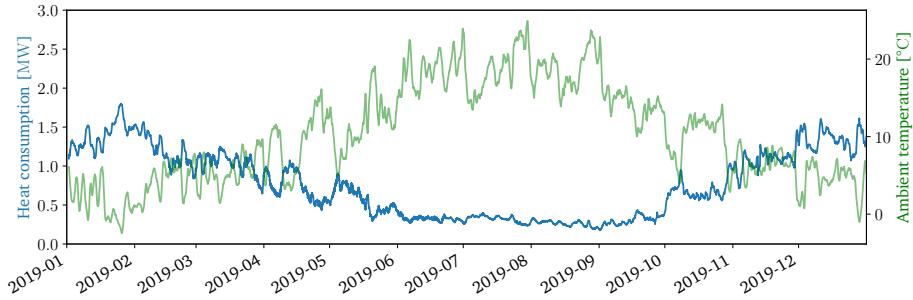


Fig. 6.7: District heating consumption in CITY2 for 2019 together with ambient temperature (daily average).

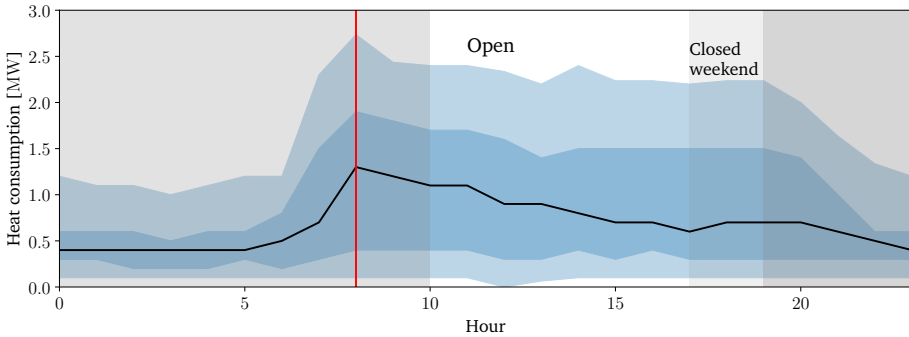


Fig. 6.8: District heating consumption in CITY2 for 2019. Plotting the median day (black) and the [25;75] and [1;99] percentile brackets.

6.2.1 Load-shifting potential from exploiting thermal mass

No deactivation experiment has been conducted in CITY2 in order to investigate the load-shifting potential. While CITY2 and Kolding Storcenter are very different in both HVAC layout and consumption profile, the results from Kolding Storcenter can still provide hints as to what is potentially achievable

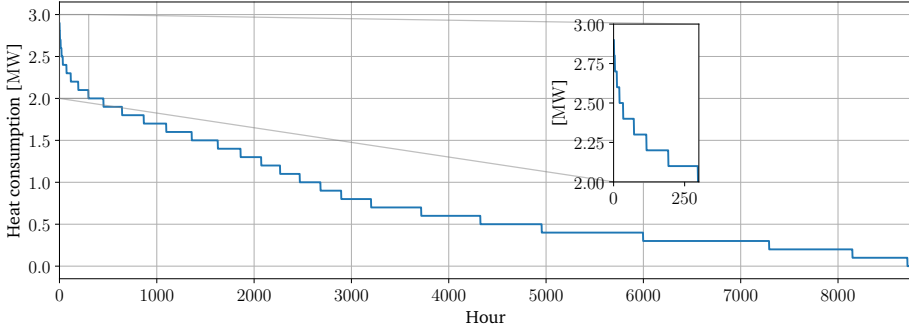


Fig. 6.9: Load Duration Curve of district heating consumption in CITY2 for 2019.

in CITY2. In Kolding Storcenter, the shop temperature and CO₂ levels only increased slightly over 1 h with limited ventilation and no cooling on a day with an ambient temperature of 10 °C. It should therefore be equally possible to do load-shifting on an hourly basis in CITY2.

For heating consumption this would amount to load curtailment in the order of 1 MW to 2 MW. This could be a relevant load-shifting service in the time span between 17:00 and 20:00, where the district heating network is loaded due to extra hot water and heating consumption in residential buildings.

In CITY2, cooling is supplied by one central cooling plant. While the power consumption has not been measured on an hourly basis, a model of the power consumption was estimated based on knowing the total cooling capacity and the fitted model for the chiller in Kolding Storcenter (see **Paper F**). The model proved adequate when integrating power consumption to evaluate energy consumption on a monthly basis. Knowing this model and the assumption of load-shifting on an hourly basis, it is possible to calculate an equivalent potential for load-shifting as:

$$\frac{\dot{Q}_{\text{cool,CITY2,cap.}}}{\dot{Q}_{\text{cool,chiller,cap.}}} = \frac{2700 \text{ kW}}{185 \text{ kW}} = 14.5$$

$$14.5 \cdot 4 \text{ kW} = 58 \text{ kW}$$

Or by first calculating the total load-shifting potential by the chillers in Kolding Storcenter (scaling by number of chillers) as $18 \cdot 4 \text{ kW} = 72 \text{ kW}$ and then scaling this by $\dot{Q}_{\text{cool,CITY2,cap.}} / \dot{Q}_{\text{cool,KSC,cap.}} = 2700 \text{ kW} / 3500 \text{ kW} \approx 0.75$, giving $0.75 \cdot 72 \text{ kW} = 54 \text{ kW}$.

In both cases giving a potential on the order of 50 kW.

For ventilation, a monthly consumption of $\approx 90 \text{ MWh}$ is known. Knowing the operating hours of the AHUs (see **Section 2.2**) the average power consumption is estimated to be 300 kW. Thus potentially providing a curtail-

ment in this order of magnitude.

6.2.2 Unlocking the flexibility

Given the HVAC setup described for CITY2 in **Section 2.2** and **Section 4.3**, multiple ways of unlocking energy flexibility have been identified. These include for heat demand:

- Limit flow in given time slot
- Manipulate forward temperature and/or flow in given time slot

And for electricity demand:

- Turn off/on cooling plant in given time slot
- Manipulate forward temperature setpoint for cooling plant in given time slot
- Turn off/on AHUs in given time slot
- Manipulate with flow of AHUs in given time slot

Compared to Kolding Storcenter, there is limited options for manipulating with flexibility on a shop-level, as there is not the same level of control authority in CITY2. The implementation barrier for unlocking flexibility is, compared to Kolding Storcenter, lower as both cooling and heating is central to the entire shopping center. This allows for easily introducing a large amount of flexibility with a minimum implementation surface through a piggybacking-approach as described in **Chapter 3**. To unlock flexibility from the AHUs, all relevant AHUs setpoints need to be exposed in the BMS. However, this also provides a higher level of granularity, as not all shops need be affected.

7 | Conclusion

The research results of this Ph.D. study have been presented in the previous chapters, along with the details in the six papers. In this chapter, a discussion and conclusion on the results is presented. Following, suggestions for future work are given.

7.1 Discussion and conclusions

In the following, discussions and conclusions based on each of the research objectives is presented.



Investigate feasibility of interfacing with existing building control

A major part of the SEBUT project and hence also a major part of this Ph.D. study was dedicated to this research objective. To introduce new building control in the existing building stock, a practical and low-effort method for interfacing with existing buildings has to be available. This was treated in **Chapter 3**, showing how open communication protocols within BMS allow for third parties to interface using the existing infrastructure. While proprietary solutions still exist and are being implemented, open protocols and initiatives such as BACnet have gained the majority of the market share.

It is therefore not guaranteed that it is possible to directly interface with an arbitrary building's BMS, but a large share of the existing building stock feature open protocols and here *piggybacking* on the existing infrastructure is directly applicable. As several control experiments have shown, both in **Chapter 3** and the results from **Paper E** (summarized in **Section 5.2.1**), this is a feasible way of introducing new control algorithms.



Formulate a model for both simulation and control purposes

The modeling effort was treated in **Chapter 4**, presenting a graph-based

multi-zone model, capable of capturing the important zone temperature dynamics, e.g. shop temperature dynamics in the context of shopping centers. This multi-zone model was the main contribution of **Paper A**. One important observation in the context of shopping centers is how dominant display lighting is. As display lighting in the case studies – at the time of writing – is not LED, the resulting internal heat gains observed are immense. This has the effect, that terms such as thermal interaction between zones and occupancy becomes insignificant in the temperature dynamics. However, with the anticipated future shift to LED lighting these terms can not simply be neglected.

Besides modeling the zone (or shop) temperature dynamics, models of (among other) supply temperature dynamics for two very different HVAC systems have been presented. Both models have been posed using the knowledge that could be extracted from the existing BMS. This approach can severely lower the performance of a fit to measurements, but as this would be the case in a retrofit situation it is an important consideration. As no open-loop system identification experiments were conducted, the parameter estimation was difficult and had to rely a great deal on table look-up and knowing the dimensions of e.g. shops. The fit to measurements obtained were deemed adequate for the control purposes of this thesis, as the purpose was not a perfect simulation model but a model "good enough" for evaluation of potential control strategies and for the basis of model-based control designs.



Investigate the use of Model Predictive Control

To propose alternative methods to the state-of-the-art, MPC, it was necessary to investigate the use of MPC. This was treated in both **Chapter 5** in terms of energy-efficient control and in **Chapter 6** in terms of exposing energy flexibility. The simulation results from using MPC have been very promising in both cases, but it is the author's opinion that the modeling work required highly defeats the application. It may deliver the best performance, but as concluded in **Paper F** simpler methods can recover 90 % of the performance – avoiding the time-consuming modeling work and providing more operator transparency, considering a method with less complexity. One could argue, that the remaining 10 % are important, but another important takeaway is, that these comparisons are based on simulation results. Factoring in reality, the likelihood that this gap is narrowed down even further is worth considering. It is not unrealistic for a more simple solution to demonstrate better results in reality where the benefits of e.g. MPC could be diminished.

One caveat is, that evaluation of simpler methods to expose energy flexibility has not been done, and hence it can not here be concluded whether these can be as attractive.



Propose an alternative method to introduce energy efficiency

This objective is treated in **Section 5.2**, summarizing the work in **Paper D**, **Paper E** and **Paper F**. An alternative method has been proposed, the bulk of the method being a hierarchical control architecture suitable for complex HVAC systems such as the ones seen in the two shopping center case studies. The method has shown promising results, especially through the inclusion of ILC, which was specifically treated in **Paper F** and through the experimental study conducted and reported on in **Paper E**. However, the most important result from this research is the fact that an alternative method can recover 90 % of the performance of a close-to-ideal MPC in simulations – making it very likely that this gap could be even smaller in a real-world case.



Investigate potential for energy flexibility in shopping centers

The potential for energy flexibility in shopping centers was treated in **Chapter 6**. The potential was investigated based on historical consumption data, a deactivation experiment and simulation studies of an MPC to directly control power consumption in a given time-slot without violating thermal comfort constraints. The MPC study was specifically reported on in **Paper B**.

From historical consumption data it seems very likely, that it is possible to shift consumption from expensive morning hours. Generally, both heating and cooling is for both case studies turned on very early in the morning, aligning with a morning peak in SPOT price of electricity. It could be very beneficial to shift the load closer to opening hours. Besides this, there is a general potential for introducing control based on SPOT prices, as seen from correlation analysis between consumption and SPOT price data.

From a deactivation experiment and from the results in **Paper B**, it seems very likely that a load-shifting service in the order of 2 W/m^2 to 3 W/m^2 for a period of 1 h can be provided. This is $\approx 100 \text{ kW}$ to 150 kW for Kolding Storcenter and $\approx 190 \text{ kW}$ to 280 kW for CITY2. However, it is important to note that the implementation of energy-efficient control will lower the potential for energy flexibility, as the consumption will be decreased. This will on the other hand open up to not provide a curtailment service, but instead increase the consumption in a given hour to alleviate over-generation in the grid. Whether these magnitudes are large, is difficult to conclude on, but given a combined area of all Danish shopping centers estimated as $2\,000\,000 \text{ m}^2$, the scale is 4 MW to 6 MW , which is significant. While it is technically possible to unlock this flexibility, the market is still not ready and further regulations are needed.

7.2 Conclusion

Summarizing the above, the main contribution of this thesis has been to bridge the gap between building control research and industry adoption, by constraining the work conducted to realistic conditions met in a building control retrofit. This constraint has been successfully applied through both the practical research of this thesis, in how to actually interface with existing buildings, in the modeling work undertaken and in the proposed control methodology. While research into the application of complex control methods is important to tackle increasingly complex problems, in the author's opinion it is equally valuable that research is conducted within tractable methods.

To tackle the climate crisis, it is important not to get caught up in chasing the last 10 %. One can not stress enough how important it is that measures are taken to reduce the energy consumption of buildings and equally, that measures are taken to make sure that buildings can adapt to the increasingly stochastic energy generation. Both of these problems are *control problems* for which a myriad of solutions exist. This thesis has sought to strike a blow for the tractable solutions.

7.3 Suggestions for future work

The overall vision that has been considered in this thesis is the formulation of an overarching control methodology, that is capable of controlling all the integrated energy systems in existing buildings, simply by interfacing with the existing infrastructure. This includes the control of heating, cooling and ventilation units in an energy optimal way, while at the same time aggregating and exposing available energy flexibility – both in terms of electricity and district heating. The method should be general enough to be re-used – this including the practicalities of how it is applied to a specific building – and it has to be cost-effective, to deliver on the promise that application of new control algorithms is a key enabler to deliver on climate targets.

7.3.1 Tangible suggestions for future work

While experimental validation was conducted in Kolding Storcenter as reported in **Paper E**, the experiment still only covers part of the shopping center and was only operating during winter. Thus, future work would include more elaborate experimental validation that potentially could embrace an entire shopping center and with more varied ambient conditions. To properly demonstrate the general application of the proposed control methodology, it

7.3. Suggestions for future work

would require also doing experimental validation in another shopping center – or another building. This could to some extent also be covered by e.g. a Hardware-in-the-Loop laboratory setup. Furthermore, **Paper F** introduces ILC, which is only evaluated in simulation studies. As the literature is sparse when considering experimental evaluation of ILC within building control this would be a natural step for future work.

In line with experimental validation of ILC, it should be researched whether a simple ILC with a forgetting factor is good enough – or whether e.g. a database-driven approach as in [35] should be considered. There could also be a potential for higher-order ILC which would weight e.g. yesterday's contribution and the contribution from a week ago, to take into account weekly dynamics; different loads and opening hours in the weekend. A more theoretical line of research would be to grasp the stability and robustness when coupling ILC and an integral controller.

Regarding energy flexibility, it would be interesting to research how this could be included in the proposed control methodology. Both in terms of indirect control, taking a price signal into consideration, but equally interesting as direct control, to explicitly manipulate the power consumption – or district heat consumption – in a given time slot.

Chapter 7. Conclusion

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Part II

Papers

Paper A

Multi-Zone Modeling and Energy Efficient Control of Shopping Center Cooling

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The layout has been revised.

Abstract

In this paper we consider the problem of constructing a dynamical model for shopping center HVAC systems, suitable for proposing new high-level control designs to minimize energy consumption for the entire shopping center. We also propose a preliminary control design, to increase energy efficiency. The specific system considered in this paper, is a small section of a Danish shopping center, including three shops and their joint cooling system. The current control solution is investigated and described.

A dynamical model is constructed as a grey-box RC-equivalent model, a suitable modeling paradigm for control-oriented models that also have to be scalable. Parameters for the model have been identified through a combination of measurement data from several days of live operation and table-lookup, calculating thermal properties based on shop dimensions.

The resulting model is used to propose a preliminary control solution, to increase efficiency by utilizing a higher forward temperature. This is achieved through a control design that seeks to drive valve openings closer to fully open, while still allowing headroom for disturbance rejection. One of the main benefits of this design, is the low implementation barrier, as it does not require alterations to shop-local temperature controllers.

Simulations show that the proposed control solution works as intended, without degrading the performance of the existing shop temperature control.

1.1 Introduction

In Denmark, buildings are responsible for approximately one third of the total energy consumption[1]. Even though energy efficiency continues to improve, the main focus is typically on the building envelope itself, rather than e.g. heating and cooling equipment[2]. The problem with this focus is that energy renovation considering the envelope itself is expensive, in comparison to replacing/updating heating and cooling equipment. There is thus an untapped potential in improving heating and cooling equipment, especially considering older buildings, where an investment in energy renovation of the building envelope can be unattractive from the owner's/operator's point of view.[3][4]

Control applications to reduce energy consumption have been considered in several works, using different approaches, with the majority utilizing predictive control[2]. Given the multi-zone characteristics of many commercial buildings, decentralized and distributed control schemes have been investigated in relatively recent works. In [5], distributed model predictive control is employed to maintain zone temperatures within given comfort requirements, utilizing predictive knowledge of weather and occupancy. Distributed

model predictive control is also used in [6]. A decentralized token-based approach to control and scheduling of Heating Ventilation and Air Conditioning (HVAC) systems in multi-zone buildings is examined in [7].

Generally, the distributed/decentralized solutions suffer a performance loss compared to centralized solutions, but they are scalable, and as such offer numerical robustness when the number of zones considered is relatively large. Another important aspect regarding centralized versus distributed/decentralized is implementation, as it greatly affects the investment size for the owners/operators. A centralized solution could potentially be cheaper given the lower implementation barrier, as no alterations to the individual zones are required.

The work presented in this paper is part of the Energy Technology Development and Demonstration Program (EUDP) project denoted Smart Energy Shopping Centers (SEBUT). SEBUT develops intelligent control systems, knowledge services and tools for energy refurbishment and energy flexibility upgrades of shopping centers in Denmark. Shopping centers are responsible for approximately 25% of the combined energy consumption in the Danish retail trade sector. The approach to energy flexibility is holistic, considering indoor air quality, advanced control of indoor climate and lighting, energy consumption and supply, energy storage, use of waste heat and also user requirements, behavior and potential barriers.[8]

The main aim of this paper is to lay the ground work for a dynamic control-oriented model of a shopping center and to propose a preliminary control design in order to reduce energy consumption. Choosing a control-oriented modeling paradigm depends on the characteristics of the building in question, but for large-scale multi-zone buildings, a grey-box RC-equivalent approach is often applicable[9]. This is the approach taken in this paper.

The multi-zone model proposed in this paper, is applied to a small section of a Danish shopping center; this is done using both measurement data and table look-up of thermal parameters. With a model in place, a preliminary control design is proposed. The design seeks to increase energy efficiency, by utilizing a higher forward temperature in the shopping center cooling system. The design is evaluated through simulations.

In **Section 1.2**, the shopping center in question is accounted for and following, in **Section 1.3**, the model equations are introduced. With model equations introduced, the model is applied and parameters are identified in **Section 1.4**. **Section 1.5** describes the preliminary control design and **Section 1.6** presents results from a simulation experiment using the proposed controller. Conclusions are given in **Section 1.7**.

Notation-wise, matrices are denoted in uppercase bold, e.g. \mathbf{A} , vectors are denoted in lowercase bold, e.g. \mathbf{x} . Dependence of variables on time t , $\mathbf{x}(t)$, is implied and will not be written explicitly.

1.2 System description

As a case for this paper, Kolding Storcenter in Jutland, Denmark, is considered. In Kolding Storcenter, a demo-area has been established for the SEBUT project. The demo-area considers a small cluster of three shops and the Central Cooling Unit (CCU) responsible for these shops. In Kolding Storcenter, cooling is delivered through a fan coil unit in the shops. The CCU delivers its cooling capacity through cooled water supplied to the fan coils. A shop-local controller regulates the supply air temperature to the shop, by actuating a valve that determines the flow of cold water through the fan coil. A block diagram depicting the demo-area setup is shown in **Figure A.1**. For each shop, the room temperature, T_{shop} , and the supply temperature, T_{supply} , are measurable and the valve control signal, u_{valve} is available as input.

The current control solution consists of a shop-local controller, manipulating valve opening to regulate room temperature. This is done through the cascade PI configuration depicted in **Figure A.2**. The temperature of the cooled water supplied to the fan coil, T_{fwd} , is controlled independently of the cooling requirements of the shops. This was concluded by investigating the Supervisory Control and Data Acquisition (SCADA) system in Kolding Storcenter.

Measurements were collected directly from the SCADA system. In **Figure A.3**, shop temperature, supply temperature and valve opening is depicted, for one of the shops in the demo-area, over two days in May 2018 with summer-like weather conditions. Opening hours are from 10:00 to 20:00 and night-setback is implemented for the shop-local controllers.

From the measurements, it is clear that shop temperature rises throughout the day, indicating that there may be capacity problems in the system. Looking at the supply temperature; it is maintained at 14 °C without saturating the valve opening (for the most parts). From the SCADA system it was identified, that 14 °C is the minimum allowable supply temperature.

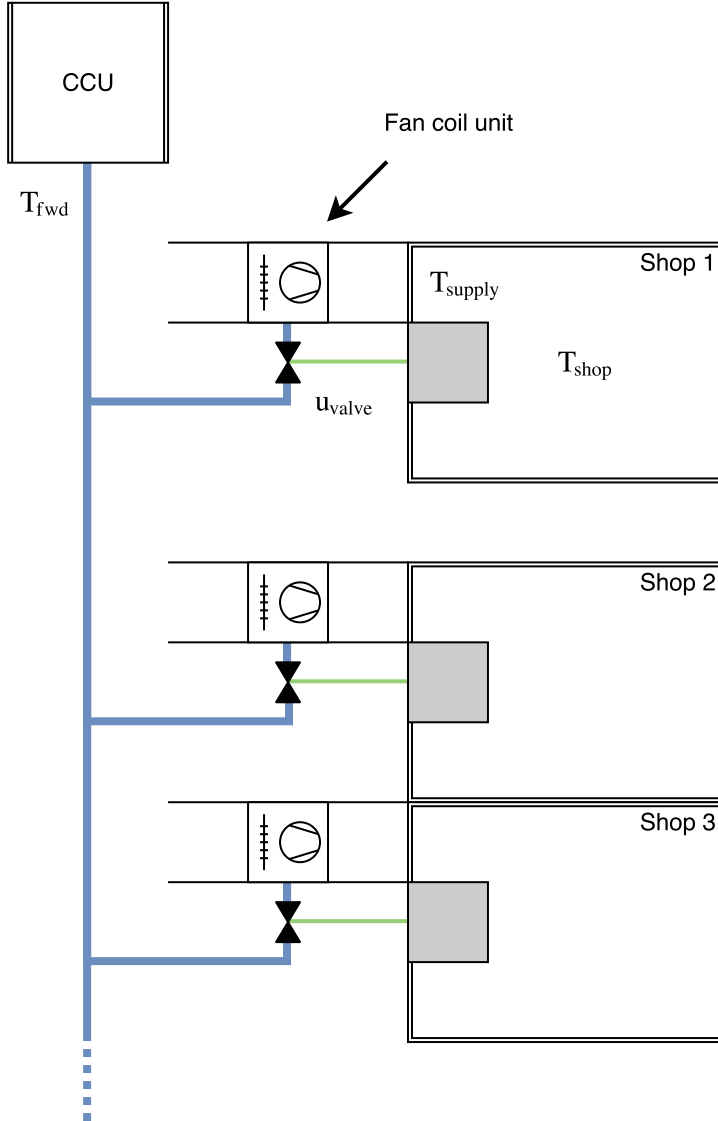


Fig. A.1: System layout of demo-area, depicting the three shops and the CCU. Shop 1 is intentionally not adjacent to Shop 2 and Shop 3, as a hallway separates them. The return flow is not depicted in this diagram.

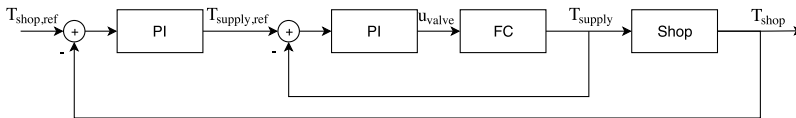


Fig. A.2: The shop-local controller is two PI regulators in a cascade configuration. The FC block is the fan coil unit.

1.2. System description

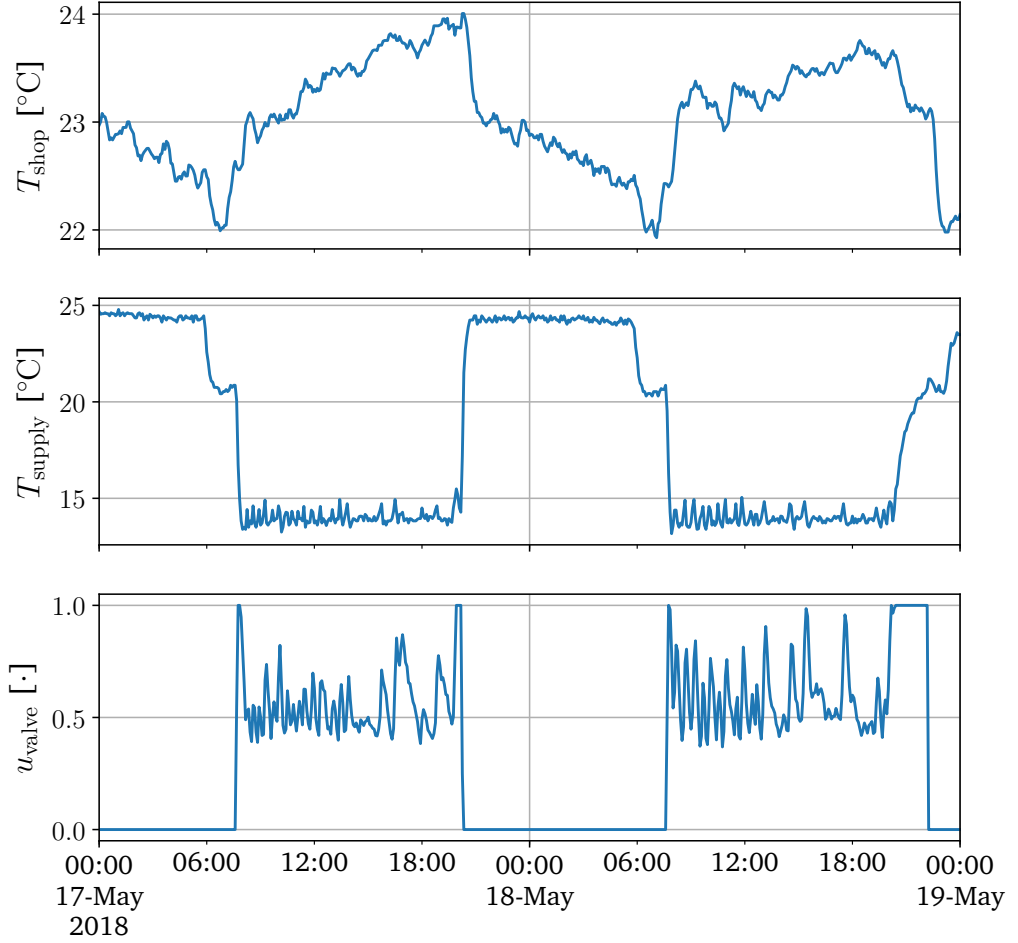


Fig. A.3: Initial measurements from the demo-area in Kolding Storcenter. Shop temperature, supply temperature and valve opening for *Shop 1* in the demo-area.

1.3 Model

The purpose of the model is to capture the most important dynamics in order to design control strategies that can significantly improve energy efficiency. Since the potential is to consider entire shopping malls, the model also has to be scalable. The model will consider the central cooling, the fan coil units, the shops and hallways/common area separating the shops. Heat flows into a thermal zone are positive, while heat flows leaving a thermal zone are negative. The system is structurally very similar to the one in [10], which has served as inspiration.

1.3.1 Shop temperature model

At first we consider the thermal dynamics of a single shop:

$$C_{\text{shop},i} \dot{T}_{\text{shop},i} = \dot{Q}_{\text{adjacent},i} - \dot{Q}_{\text{fancoil},i} + \dot{Q}_{\text{int},i} \quad (\text{A.1})$$

where $C_{\text{shop},i}$ is the lumped thermal capacitance of the shop, $T_{\text{shop},i}$ is the room temperature of the shop and $\dot{Q}_{\text{adjacent},i}$ is the heat flow to/from surrounding shops and or hallways/common area – commonly denoted zones. $\dot{Q}_{\text{fancoil},i}$ is the heat flow removed by the fan coil unit and $\dot{Q}_{\text{int},i}$ models the internal heat gain, e.g. heat gain from occupancy, lighting and appliances.

Similarly, we consider the thermal dynamics of hallways/common area:

$$C_{\text{hall},i} \dot{T}_{\text{hall},i} = \dot{Q}_{\text{adjacent},i} + \dot{Q}_{\text{int},i} \quad (\text{A.2})$$

where $C_{\text{hall},i}$ is the lumped thermal capacitance of the hallway and $T_{\text{hall},i}$ is the room temperature in the hallway. Equivalently to the shop dynamics, there is a term for heat flow to/from the adjacent zones and from internal heat gain. The main difference is that for hallways we do not model cooling, as the focus is on the shops.

The thermal dynamics of the fan coils are governed by the following state equation:

$$C_{\text{fancoil},i} \dot{T}_{\text{supply},i} = \dot{Q}_{\text{fancoil},i} - \dot{Q}_{\text{CCU},i} \quad (\text{A.3})$$

where $C_{\text{fancoil},i}$ is the lumped thermal capacitance of the fan coil unit and $T_{\text{supply},i}$ is the temperature of the supply air to the shop, in which the fan coil unit is mounted. The heat flow to the fan coil is equivalent to the heat flow removed from the shop, $\dot{Q}_{\text{fancoil},i}$, and $\dot{Q}_{\text{CCU},i}$ is the heat flow removed from the fan coil, by the supplied cold water from the CCU.

To model the heat exchange between adjacent zones, we consider a thermal resistance between the zones. This lets us write $\dot{Q}_{\text{adjacent},i}$ as:

$$\dot{Q}_{\text{adjacent},i} = \sum_{j \in \mathcal{N}_i} \frac{T_j - T_i}{R_{i,j}} \quad (\text{A.4})$$

where \mathcal{N}_i is the set of all neighboring zones and $R_{i,j}$ is the thermal resistance between the zone in question, i , and its j -th adjacent neighbor.

We model the remaining heat flows as:

$$\dot{Q}_{\text{fancoil},i} = \dot{m}_{\text{air},i} c_{p,\text{air}} (T_{\text{supply},i} - T_{\text{shop},i}) \quad (\text{A.5})$$

$$\dot{Q}_{\text{CCU},i} = \dot{m}_{\text{water},i} c_{p,\text{water}} (T_{\text{fwd}} - T_{\text{supply},i}) \quad (\text{A.6})$$

where $\dot{m}_{\text{air},i}$ is a fixed parameter, as the fan speed is not controllable. Specific heat capacity for air and water is given by $c_{p,\text{medium}}$. The flow of water, $\dot{m}_{\text{water},i}$ is controllable through a valve. The pressure difference is assumed constant, together with the density of the refrigerant (water, no phase change). The valve characteristics are modeled to be linear:

$$\dot{m}_{\text{water},i} = K u_{\text{valve},i} \quad (\text{A.7})$$

Assuming a linear valve characteristic is for this model acceptable for two apparent reasons; (1) we have no information on the actual characteristics and (2) the valve opening is controlled by a regulator.

The dynamics of T_{fwd} are not modeled, it is simply left as an input.

1.3.2 Scalability considerations

Now, the above state equations are in a suitable form when considering a low number of zones, but not for modeling an entire shopping mall, with the potential of hundreds of zones. Thus, the equations have been simplified through a graph theoretical view. We collect all the thermal zones, shops and hallways, as nodes in the graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$. An edge between two zones exists if they are physically adjacent. Furthermore, we let the edges be weighted by $G_{i,j} = 1/R_{i,j}$ – the thermal conductance between the zones. Now, we form the adjacency matrix:

$$\mathbf{A}(\mathcal{G}) = [a_{i,j}] = [G_{i,j}] \in \mathbb{R}^{N_{\text{zones}} \times N_{\text{zones}}} \quad (\text{A.8})$$

where $G_{i,j} \neq 0$ if zone i and j are adjacent. Furthermore, let $d(i) = \sum_j G_{i,j}$ denote the degree of the i -th node and let $\mathbf{D}(\mathcal{G}) = \text{diag}(d(i))$, then we can form the Laplacian matrix of \mathcal{G} as:

$$\mathbf{Q}(\mathcal{G}) = \mathbf{D}(\mathcal{G}) - \mathbf{A}(\mathcal{G}) \quad (\text{A.9})$$

We can now express the vector of heat flows between zones as:

$$\dot{\mathbf{Q}}_{\text{adjacent}} = -\mathbf{Q}(\mathcal{G}) \mathbf{T} \quad (\text{A.10})$$

$$\mathbf{T} = [\mathbf{T}_{\text{shop}} \quad \mathbf{T}_{\text{hall}}]^T \quad (\text{A.11})$$

where $\mathbf{T}_{\text{shop}} \in \mathbb{R}^{N_{\text{shops}}}$ and $\mathbf{T}_{\text{hall}} \in \mathbb{R}^{N_{\text{halls}}}$ are the vectors collecting all the shop temperatures and hall temperatures, respectively. With this result, we can reduce our state equations to:

$$\mathbf{C} \dot{\mathbf{T}} = -\mathbf{Q}(\mathcal{G}) \mathbf{T} - \dot{\mathbf{Q}}_{\text{cool}} + \dot{\mathbf{Q}}_{\text{int}} \quad (\text{A.12})$$

$$\dot{\mathbf{Q}}_{\text{cool}} = [\dot{\mathbf{Q}}_{\text{fancoil}} \quad \mathbf{0}]^T \quad (\text{A.13})$$

$$\dot{\mathbf{Q}}_{\text{fancoil}} = \dot{\mathbf{m}}_{\text{air}} c_{p,\text{air}} (\mathbf{T}_{\text{supply}} - \mathbf{T}_{\text{shop}}) \quad (\text{A.14})$$

$$\mathbf{C}_{\text{fancoil}} \dot{\mathbf{T}}_{\text{supply}} = \dot{\mathbf{Q}}_{\text{fancoil}} - \dot{\mathbf{Q}}_{\text{CCU}} \quad (\text{A.15})$$

where \mathbf{C} is a diagonal matrix with $C_{\text{shop},i}$ and $C_{\text{hall},i}$ in the diagonal. \dot{Q}_{cool} encapsulates \dot{Q}_{fancoil} , which also handles potential cooling of the hallway. This is not considered in this model, however.

1.4 Model applied to demo-area

Parameters have been estimated using table-lookup[9] and measurement data through manual fitting, comparing temperature responses from simulations¹ to the measured temperatures. The simulations are closed loop simulations, simulating the supply temperature control implemented in Kolding Storcenter. The resulting comparison between simulated model and measurements is given in **Figure A.5**.

The desire is not a very accurate high-fidelity model, and as such the goal has simply been to find a parameter set which lies within the correct order of magnitude. The process was completed for a single shop, *Shop 1*, until a satisfactory fit was obtained. These parameters have then been scaled for *Shop 2* and *Shop 3*, given the shop sizes.

The floor plan for the demo-area is depicted in **Figure A.4**, with the graph \mathcal{G} of thermal zones imposed on top. As *Shop 1* is large, it has been divided into two thermal zones. *Shop 2* and *Shop 3* are given a single thermal zone. The hallway area, separating *Shop 1* from *Shop 2* and *Shop 3* has been discretized to include seven thermal zones. *Shop 1* measures approximately 1000 m², divided equally in the two thermal zones. *Shop 2* and *Shop 3* both measure approximately 250 m².

Flow measurements of fan coils have been conducted, giving an approximate total mass flow for *Shop 1* of 3 kg/s; $\dot{m}_{\text{air}} = 1.5$ kg/s for each zone in *Shop 1*. Under peak cooling conditions with a supply temperature of 14 °C and a shop temperature of 23 °C, this gives a cooling capacity of 27 kW. This indicates, that the internal heat gain, \dot{Q}_{int} , lies within this size. The shop temperature is, given the measurements obtained (**Figure A.3**), largely dominated by \dot{Q}_{int} which based on observations at Kolding Storcenter, is due to lighting. Thus, for simulations \dot{Q}_{int} is introduced as a step from 0 W to 27 kW; 13.5 kW for each of the two zones.

To be able to deliver this cooling capacity, the valve characteristic constant has been chosen as $K = 1.125$; this balances the system in peak cooling conditions, delivering 14 °C supply temperature at a valve opening of 0.5, assuming a CCU forward temperature reference of ≈ 8 °C, which was identified from the SCADA system at Kolding Storcenter. No data of the forward temperature is however available from the same period as the rest of the measurements.

Thermal capacitances were obtained using table lookup and an estimate of shop volume. Thermal resistances were obtained through estimating the area of either open facades or interior walls between adjacent zones. The thermal conductance between the hallway zones and shop zones was set as 100 W/K, as was the thermal conductance between hallway zones in-between. This is justified by the large open facades of the shops. The conductance between *Shop 2* and *Shop 3* was set as 50 W/K.

¹A simulation environment has been built in Python using SciPy[11].

1.5. Energy optimization through control

Given the results in **Figure A.5**, the model fits measurements to an acceptable degree, given the limited information and the simplified parameter identification process.

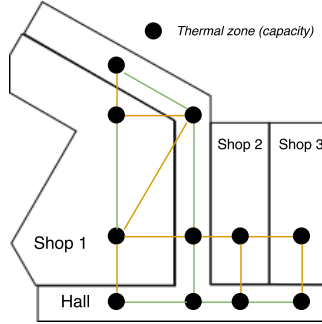


Fig. A.4: Demo-area in Kolding Storcenter, with a graph of thermal zones imposed on top. The edges between the nodes (zones) determine the thermal interaction. The edges are colored to distinguish interaction between shops and hallway (orange) and hallways/shops in-between (green).

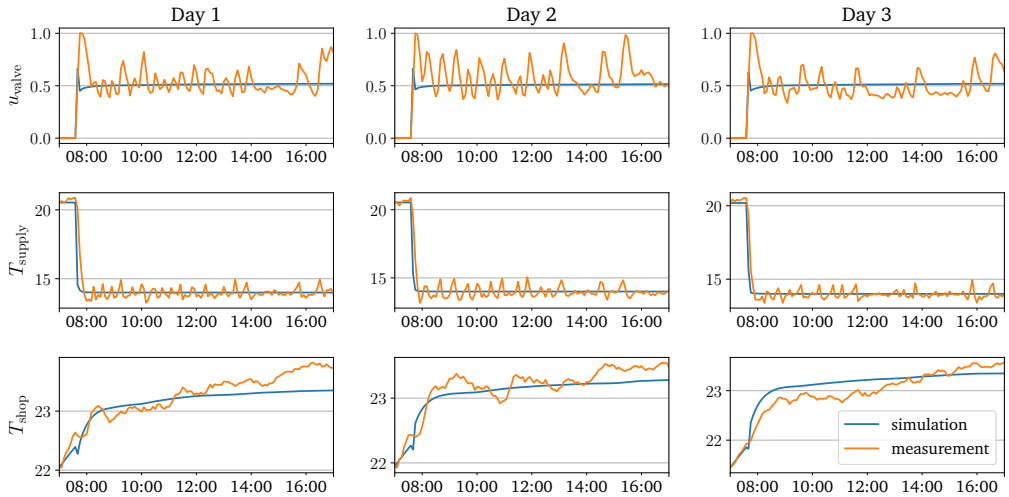


Fig. A.5: Comparison between simulated model with identified parameters and measured data, across three different days (2018-05-17, 2018-05-18, 2018-05-23) with summer conditions. Generally a good fit. The biggest uncertainty lies in shop temperature; since this is not actively controlled as the supply temperature and given the many disturbances not known in e.g. \dot{Q}_{int} .

1.5 Energy optimization through control

A key aspect of the SEBUT project, is that the designed control solutions have to be applicable to already existing building setups, re-using as much as possible, in an attempt to keep the implementation minimal and the impact maximal. As such,

this paper introduces a preliminary control solution, that does not alter the shop-local controllers. Instead, it is desirable to investigate the introduction of forward temperature setpoint scheduling.

One metric for energy efficiency in refrigeration systems is the Coefficient of Performance (COP), which can be expressed as:

$$\text{COP} = \frac{\dot{Q}_{\text{refrig}}}{P_c} \quad (\text{A.16})$$

where \dot{Q}_{refrig} is the heat removed from the system by the refrigeration system and P_c is the power consumed by the refrigeration system. In our case:

$$\dot{Q}_{\text{refrig}} = \sum_i \dot{Q}_{\text{CCU},i} = \dot{m}_{\text{tot}} c_{p,\text{water}} (T_{\text{fwd}} - T_{\text{ret}}) \quad (\text{A.17})$$

$$\dot{m}_{\text{tot}} = \sum_i \dot{m}_i \quad (\text{A.18})$$

$$T_{\text{ret}} = \frac{\sum_i \dot{m}_i T_{\text{supply},i}}{\sum_i \dot{m}_i} \quad (\text{A.19})$$

The theoretical COP of the CCU is dependent on forward temperature and ambient temperature (heat reservoir), as given by the COP for a Carnot cycle:

$$\text{COP}_{\text{max}} = \frac{T_{\text{fwd}}}{T_{\text{amb}} - T_{\text{fwd}}} \quad (\text{A.20})$$

Thus, the efficiency increases, as the forward temperature approaches the ambient temperature. This is a crude simplification for a chiller, but it reveals a desire to let the forward temperature be as close to the ambient temperature, while still enabling the cooling capacity demand by the fan coil units. This expression for COP_{max} is however only valid in the case where ambient temperature is higher than the temperature inside, limiting it to cooling of the shops during the summer. In the case where the ambient temperature is lower than the inside temperature, there is no theoretical limit on COP_{max} . This implies that Eq. (A.20) will eventually have to be replaced by a combined expression that takes both cooling and heating into account. That is beyond the scope of the preliminary work in the present paper, however.

This paper proposes a centralized control solution, regulating the forward temperature such that the fan coil unit with the highest cooling demand, has its valve opening almost saturate (90% open), leaving some headroom for disturbance rejection. This approach is similar to the one taken in [12]. The control solution is depicted in **Figure A.6**.

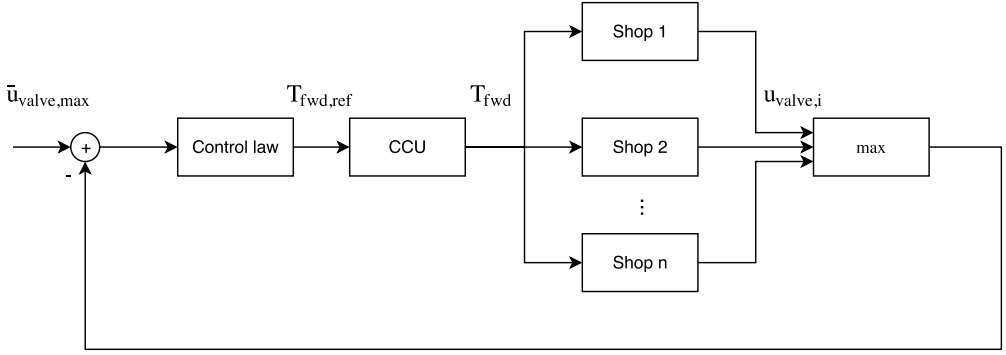


Fig. A.6: Control solution to drive valve opening close to saturation, through regulation of forward temperature.

The benefits of this control solution is especially the low barriers to implementation, as the shop-local controllers remain untouched. The controller is in this paper a regular PI controller, giving rise to the control law:

$$e = \bar{u}_{\text{valve,max}} - \max(\mathbf{u}_{\text{valve}}) \quad (\text{A.21})$$

$$T_{\text{fwd,ref}} = K_p e + K_i \int e \, dt \quad (\text{A.22})$$

where \max is the operation that picks out the maximum element in the vector given, and $\bar{u}_{\text{valve,max}} = 0.9$. The \max operation introduces switching-behavior to the system. Stability-wise, this can be analyzed using standard hybrid system analysis[13], but such an analysis is not within the scope of this paper.

1.6 Simulation studies

A simulation has been carried out to investigate the difference between a constant forward temperature and controlling the forward temperature, through the suggested control strategy. The simulation mimics the daily behavior of the system, just as for the parameter estimation simulations. The only two differences being that at 11:00, the otherwise constant forward temperature of cold water is instead regulated using the scheme described in **Section 1.5** – and that measurement noise is modeled for the supply temperature, to introduce a stochastic element in the simulation. The measurement noise is sampled from a normal distribution with $\mu = 0$ and $\sigma = 0.05$, which is the approximate noise level identified in the measurement data. The results of the simulation are depicted in **Figure A.7**.

It should be noted, that the local PI controllers maintain the shop temperatures at the references, even with the central forward temperature control enabled. The forward temperature is raised from the 8 °C to around 10 °C, which could be a significant efficiency increase, especially given the peak cooling conditions – this is also indicated by the increase in the maximum COP.

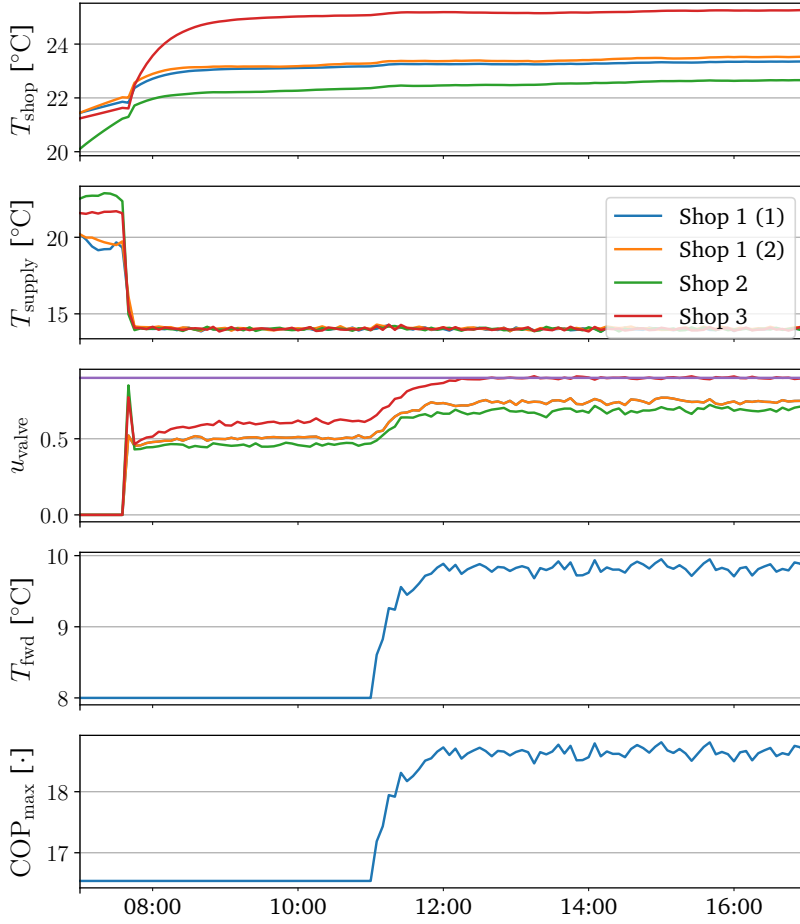


Fig. A.7: Simulation comparing the effects of a constant forward temperature with the proposed control solution, driving valve opening towards (almost) full opening. The purple line shows the valve opening reference of 0.9. COP_{max} is calculated assuming T_{amb} of 25 °C.

1.7 Conclusions

This paper has laid the ground work for a dynamical model of a shopping center. It has proposed a scalable multi-zone model and applied it to a demo area in a danish shopping center; estimating parameters through measurement data and table-lookup with acceptable results.

Using the model, a preliminary control design was proposed to allow the system to run using higher forward temperatures, for better energy efficiency. Through simulations, the design shows promising results; most importantly given the low implementation barriers. The simulation presented in this paper showed, that the introduction of this central controller would not degrade the performance of the shop-local controllers, allowing a gain in energy efficiency through a relatively simple central implementation.

Future work includes collecting data on power consumption, to pose an operational model of COP. This will allow conclusions to be drawn on the energy efficiency improvements of the control scheme proposed. Also, it is necessary to further investigate both scalability of the model – especially in regards to the inclusion of hallway zones – but also flexibility, as the desire is to reuse the framework for different shopping centers.

Acknowledgement

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Paper B

Energy Flexibility for Systems with large Thermal Masses with Applications to Shopping Centers

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Pierre Vogler-Finck, Jakob Stoustrup

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The layout has been revised.

Abstract

In this paper we propose a scheme for managing energy flexibility in buildings with significant thermal masses and centralized climate control, such as commercial buildings, which can be used to provide ancillary services to the local electrical system (demand response). The scheme relies on being able to manipulate the forward flow temperature in the climate control system along with heating/cooling of zones of the building, and thereby controlling the electrical power consumption of the system. A Model Predictive Control law is formulated to provide pre-storage of thermal energy in the manipulated zones without violating comfort requirements.

The scheme is illustrated on a case study of a Danish shopping center, from which actual heating/cooling data have been collected for identification of thermal dynamics. The Coefficient of Performance of the system's chiller is assumed to have a known dependence on flow and temperature, which is exploited to relate electrical power consumption to forward flow temperature. Simulation studies indicate potentials for significant power curtailment, in the order of 100 kW for one hour for the shopping center as a whole.

2.1 Introduction

The increasingly stochastic electricity production in Denmark[1] imposes new requirements for balancing the production and consumption of energy. As conventional power production is replaced with renewables, so is to a large extent the possibility of providing grid balancing ancillary services. This can, however, be countered by using flexible consumption to provide the necessary grid balancing.

Buildings comprise approximately 2/3 of the total electricity consumption in Denmark [1] and can provide potential load-shifting grid balancing ancillary services, by exploiting thermal comfort requirements, allowing e.g. air temperatures to vary within a certain band. The duration and load magnitude of a load-shifting service is dependent on the allowable temperature fluctuations and on the time constant of the temperature dynamics. The time constant is largely dictated by the thermal capacitances.

The survey papers [2], [3] and [4] give a broad overview of the benefits of deploying thermal storages and other demand side entities for ancillary services, along with insight into various techniques for achieving that purpose.

One of the most prominent of these techniques consists of shifting electric load in time via predictive control. In [5] a control system is demonstrated that allows a pool of household heat pumps to track a power reference; providing flexible consumption while still adhering to consumer comfort requirements. In [6], a Model Predictive Control (MPC) scheme is proposed and tested in a commercial building, manipulating fan speeds to provide

flexibility. In [7] and [8] the energy flexibility of a supermarket refrigeration system and a HVAC chiller for office buildings is aggregated through a predictive control strategy that allows direct control of their combined power consumption; the work in [7] presents experimental verification where power consumption is constrained to be below a certain level.

In this paper we propose a control scheme for managing and exposing energy flexibility, in a certain class of multi-zone buildings with centralized climate control. The approach is based on an RC-equivalent dynamical model of zone temperatures, utilizing MPC with time-dependent constraints to directly manage either power or energy consumption.

The work is part of the Danish *Energy Technology Development and Demonstration Program (EUDP)* project denoted *Smart Energy Shopping Centers (SEBUT)*. The goal of SEBUT is to design intelligent control systems, achieving energy efficient and flexible operations of Danish shopping centers[9]. Given this premise, this paper examines a Danish shopping center and the proposed scheme for managing and exposing flexibility is applied to a small section of this shopping center – including implementation considerations. Simulation experiments are conducted to evaluate the scheme.

In **Section 2.2** the approach is described, including a description of the class of systems considered and how their temperature dynamics are modeled. Then, **Section 2.3** describes the specifics of how energy flexibility can be introduced using time-dependent constraints in an optimal control problem. A case-study of a Danish shopping center is presented in **Section 2.4** and case-study simulations evaluating the proposed control scheme are shown in **Section 2.5**. Conclusions are given in **Section 2.6**.

2.2 System Model

The class of systems considered, share the Heating Ventilation and Air Conditioning (HVAC) architecture depicted in **Figure B.1**; with central hydronic cooling, hydronic heating and central ventilation. Each thermal zone is equipped with local heating and cooling actuators for control of the temperature of the supplied ventilated air, enabling control of zone temperatures.

2.2. System Model

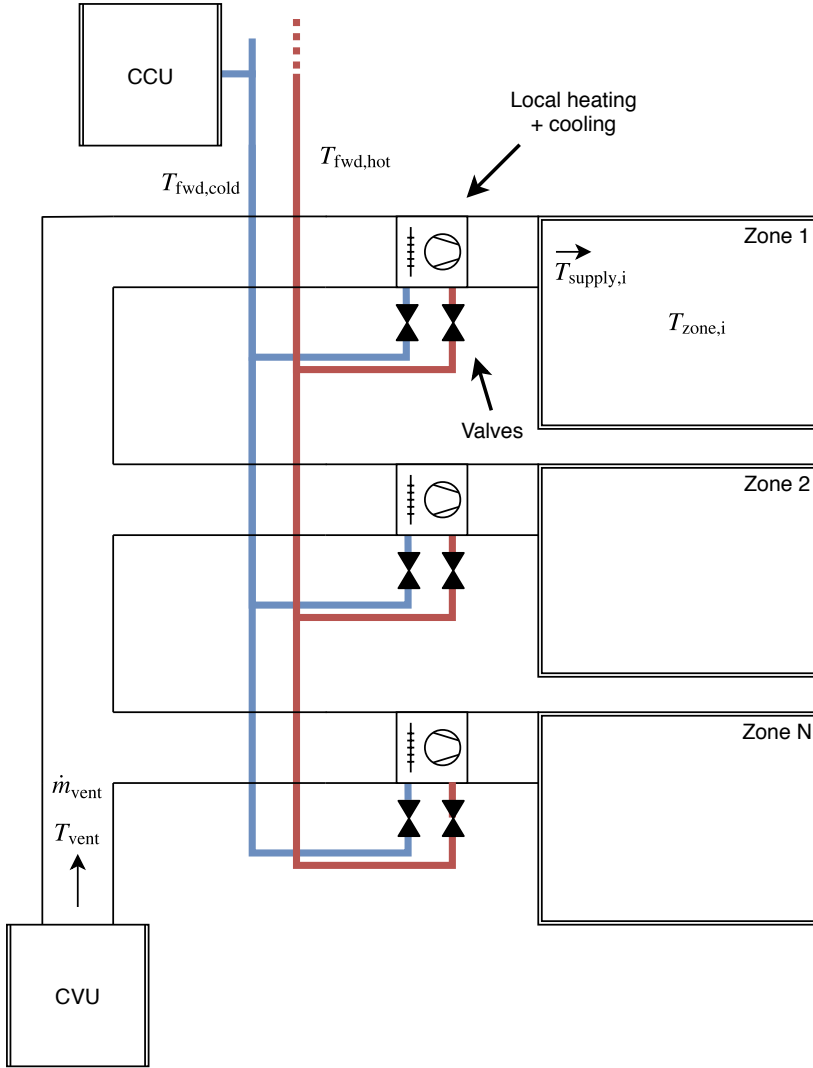


Fig. B.1: HVAC architecture for the class of systems treated. Heating and cooling enabled at zone level through distribution of both chilled and heated water to local coils. CCU (Central Cooling Unit) denotes a centralized chiller, supplying several zones with chilled water. CVU denotes a Centralized Ventilation Unit, supplying several zones with ventilated air.

2.2.1 Model of temperature dynamics

A grey-box RC-equivalent modeling paradigm is employed, treating each thermal zone as a lumped thermal capacitance. Let N be the number of thermal zones. The temperature of the i -th thermal zone is given by the

following differential equation:

$$C_{\text{zone},i} \dot{T}_{\text{zone},i} = \dot{Q}_{\text{adjacent},i} - \dot{Q}_{\text{act},i} + \dot{Q}_{\text{int},i} \quad (\text{B.1})$$

where $C_{\text{zone},i}$ is the lumped thermal capacitance of thermal zone i , $T_{\text{zone},i}$ is the temperature of the zone and $\dot{Q}_{\text{adjacent},i}$ is the heat flow to/from adjacent zones. $\dot{Q}_{\text{act},i}$ is the heat flow supplied by the local heating/cooling actuator and $\dot{Q}_{\text{int},i}$ models the internal heat gain, e.g. heat gain from occupancy, lighting and appliances. A thorough description of the details of the models is given in [10], which systematically introduces the dynamics.

The actuator heat flow, $\dot{Q}_{\text{act},i}$, is dependent on the flow of air into a zone and the temperature of that air, $T_{\text{supply},i}$. The dynamics of $T_{\text{supply},i}$ are modeled as:

$$C_{\text{act},i} \dot{T}_{\text{supply},i} = \dot{Q}_{\text{act},i} + \dot{Q}_{\text{CCU},i} + \dot{Q}_{\text{CHU},i} + \dot{Q}_{\text{CVU},i} \quad (\text{B.2})$$

where $C_{\text{act},i}$ is the lumped thermal capacitance of the actuator and $T_{\text{supply},i}$ is the temperature of the supply air to the zone. $\dot{Q}_{\text{CCU},i}$ is heat flow from central cooling, $\dot{Q}_{\text{CHU},i}$ is heat flow from central heating and $\dot{Q}_{\text{CVU},i}$ is heat flow from central ventilation. Equations for all zones are collected, by looking at the system as a graph. We collect all the thermal zones as nodes in the graph \mathcal{G} . An edge between two zones exists if they are physically adjacent. The edges are weighted by the thermal conductance between the zones. We now describe the dynamics in matrix/vector form as:

$$\dot{\mathbf{Q}}_{\text{adjacent}} = -\mathbf{Q}(\mathcal{G}) \mathbf{T} \quad (\text{B.3})$$

$$\mathbf{T} = [T_{\text{zone},1}, T_{\text{zone},2}, \dots, T_{\text{zone},N}]^T \quad (\text{B.4})$$

where $\mathbf{Q}(\mathcal{G})$ is the Laplacian matrix[11] of \mathcal{G} and \mathbf{v}^T denotes \mathbf{v} transposed. Summarizing the model as:

$$\mathbf{C} \dot{\mathbf{T}} = -\mathbf{Q}(\mathcal{G}) \mathbf{T} - \dot{\mathbf{Q}}_{\text{act}} + \dot{\mathbf{Q}}_{\text{int}} \quad (\text{B.5})$$

$$\mathbf{C}_{\text{act}} \dot{\mathbf{T}}_{\text{supply}} = \dot{\mathbf{Q}}_{\text{act}} + \dot{\mathbf{Q}}_{\text{CCU}} + \dot{\mathbf{Q}}_{\text{CHU}} + \dot{\mathbf{Q}}_{\text{CVU}} \quad (\text{B.6})$$

$$\dot{\mathbf{Q}}_{\text{act}} = \dot{\mathbf{m}}_{\text{air}} c_{p,\text{air}} (\mathbf{T}_{\text{supply}} - \mathbf{T}) \quad (\text{B.7})$$

where $\dot{\mathbf{m}}_{\text{air}}$ is the mass flow of air supplied to the zones. The combined cooling and heating loads are given by:

$$\dot{Q}_{\text{cool}} = \sum_{i=0}^N \dot{Q}_{\text{CCU},i} \quad (\text{B.8})$$

$$\dot{Q}_{\text{heat}} = \sum_{i=0}^N \dot{Q}_{\text{CHU},i} \quad (\text{B.9})$$

2.3. Direct Control using MPC

As such, the power consumption in each case can be calculated as:

$$P_{\text{cool}} = \frac{\dot{Q}_{\text{cool}}}{\eta_{\text{cool}} \text{COP}_{\text{cool}}} \quad (\text{B.10})$$

$$P_{\text{heat}} = \frac{\dot{Q}_{\text{heat}}}{\eta_{\text{heat}} \text{COP}_{\text{heat}}} \quad (\text{B.11})$$

where COP is the Coefficient of Performance (COP) and η is a general efficiency factor, covering e.g. transport loss and coil efficiencies.

It is as such possible to manipulate power consumption through changes in cooling and heating load; e.g. through forward temperature manipulation ($T_{\text{fwd,cold}}$, $T_{\text{fwd,hot}}$) or through the manipulation of zone local cooling/heating (\dot{Q}_{act}).

2.3 Direct Control using MPC

Methods for controlling flexible consumption are often classified as either direct or indirect. For direct control, it is required by the consumer to meet a specified energy consumption in a specified time-slot[12]; this can be posed in the form of a power consumption reference signal, $P_{\text{ref}}(t)$, which the consumer has to track. Indirect control is based on an incentive signal, e.g. a price signal, where the intent is to provide motivation to shift loads to periods with e.g. low price.

We consider how we can employ optimal control to enable direct control of power consumption, in order to provide a general load-shifting flexibility service. Market-wise, such a service could as an example be traded intra-day in the Nordic *regulating power market*; selling upwards or downwards regulating power for a specific hour[12] up to 45 min before the delivery hour.

In posing an optimal control problem, it is possible to include equality constraints on certain variables. Thus, it is possible to include time-dependent equality constraints on power consumption, for load-shifting through direct control. One common form of employing optimal control, is by solving an optimal control problem with a receding horizon, resulting in Model Predictive Control.

2.3.1 Model Predictive Control

For discretized and linear system dynamics, a general MPC problem can be formulated as:

$$\min_{\mathbf{u}} J = \sum_{k=n}^{n+H} l(k, \mathbf{x}(k), \mathbf{u}(k), \mathbf{y}(k)) \quad (\text{B.12})$$

subject to:

$$\mathbf{x}(k+1) = \mathbf{A} \mathbf{x}(k) + \mathbf{B} \mathbf{u}(k) \quad (\text{dynamics})$$

$$\mathbf{y}(k) = \mathbf{C} \mathbf{x}(k) + \mathbf{D} \mathbf{u}(k) \quad (\text{output})$$

state, input and output constraints:

$$\mathbf{x}_{\min} \leq \mathbf{x}(k) \leq \mathbf{x}_{\max}$$

$$\mathbf{u}_{\min} \leq \mathbf{u}(k) \leq \mathbf{u}_{\max}$$

$$\mathbf{y}_{\min} \leq \mathbf{y}(k) \leq \mathbf{y}_{\max}$$

where n is the current sample number / iteration number, l is a function mapping from states ($\mathbf{x} \in \mathbb{R}^{n_x}$), inputs ($\mathbf{u} \in \mathbb{R}^{n_u}$) and outputs ($\mathbf{y} \in \mathbb{R}^{n_y}$) to \mathbb{R} . We choose l depending on the objective of the control law.

We include our time-dependent power consumption constraint, including time-shifting to compensate for the receding horizon:

$$P(k) = P_{\text{ref}}(k - n) \quad \text{for} \quad n_{\text{on}} \leq k + n \leq n_{\text{off}} \quad (\text{B.13})$$

Or in the form of an energy constraint:

$$\sum_{k=n_{\text{on}}-n}^{n_{\text{off}}-n} P(k) = \sum_{k=n_{\text{on}}-n}^{n_{\text{off}}-n} P_{\text{ref}}(k) \quad (\text{B.14})$$

Given linear model dynamics, linear constraints, l convex and assuming a feasible solution exists, the solution found via Linear Programming methods is guaranteed to be optimal. To adhere to the power/energy constraints, the prediction horizon, H , has to be set long enough for the controller to act on the constraints and shift the load.

2.4 Case Study: Kolding Storcenter

Kolding Storcenter is one of two Danish shopping centers investigated in the SEBUT project [9].

2.4.1 HVAC setup

The HVAC system in Kolding Storcenter is made up of several HVAC hubs, with a layout similar to the one described in **Section 2.2**. Each hub supplies

a number of shops with cooling or heating, through temperature regulated air blown into the shops through fan coil units. The air is delivered from a central ventilation unit at an almost constant temperature and flow, during opening hours.

The fan coil units contain both a cooling and a heating coil, supplied with cold and hot water. Water flows through the coils are determined by electronically controlled valves. Valve opening is determined by local temperature controllers. The local temperature controllers receive setpoints through a central Building Management System (BMS) system. Local temperature controllers run with a sample time of 1 min.

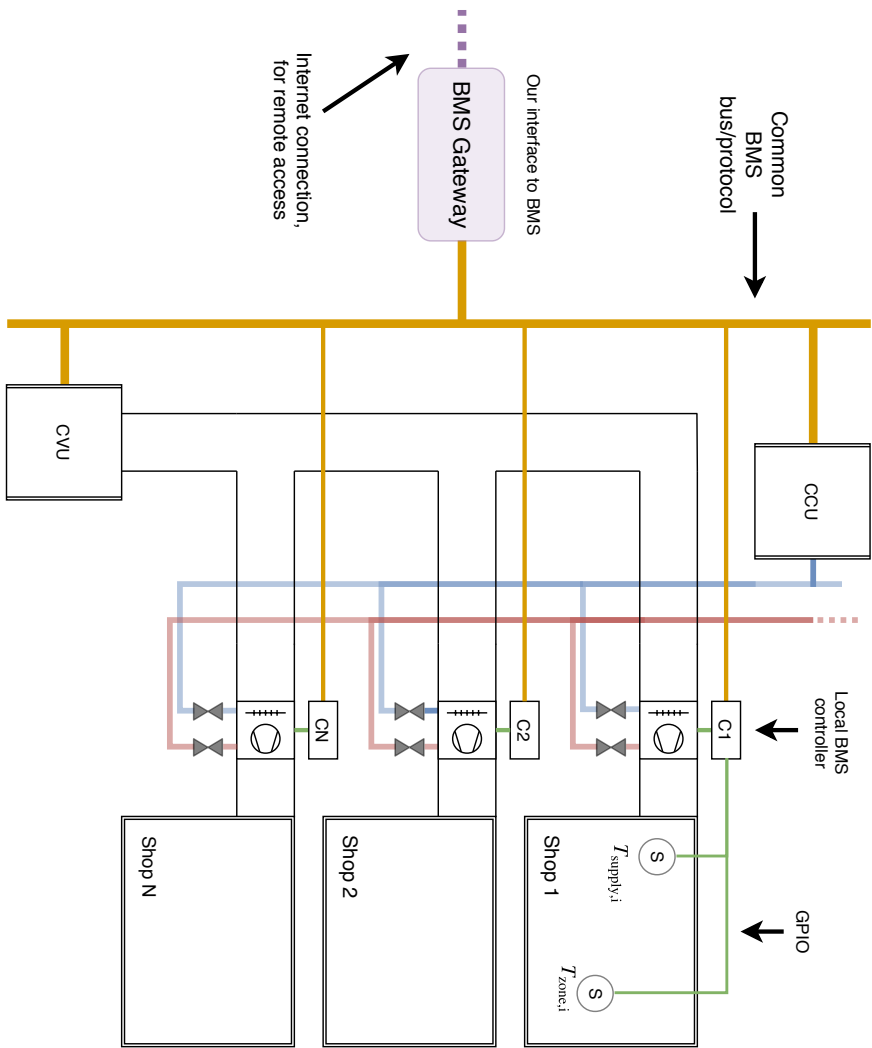
For demonstration purposes, a single hub consisting of a ventilation unit and a chiller is considered – together with three of the shops they supply. The shop layout, together with their division in thermal zones is given in **Figure B.3**.

2.4.2 System Integration

To facilitate sensor and actuator needs, we piggyback on the BMS by interfacing with the existing BMS network through the use of a *gateway unit*. Using this approach, already existing measurements and actuator signals are made available. The gateway unit allows for remote access through an Internet connection, allowing the more advanced control algorithms to be executed in e.g. a cloud-environment. The gateway unit operates with a sample time of 5 min while the BMS operates with a sample time of 1 min. A diagram sketching the approach, is given in **Figure B.2**.

Possible input signals for manipulation through the BMS include (not exclusively) setpoints for supply temperature, $T_{\text{supply},r}$, and setpoints for the forward temperature to the chiller (CCU), $T_{\text{fwd,cold},r}$. Measurements available include T_{shop} , T_{supply} and $T_{\text{fwd,cold}}$. It is not possible to manipulate fan speed for the shop fan coil units, given that the HVAC setup in Kolding Storcenter is Constant Air Volume (CAV)-based and not Variable Air Volume (VAV).

Fig. B.2: The demo-zone in Kolding Storcenter, depicting the BMS network and how it is used through a gateway unit, to re-purpose already existing sensor measurements and actuator inputs for our control purposes.



2.4. Case Study: Kolding Storcenter

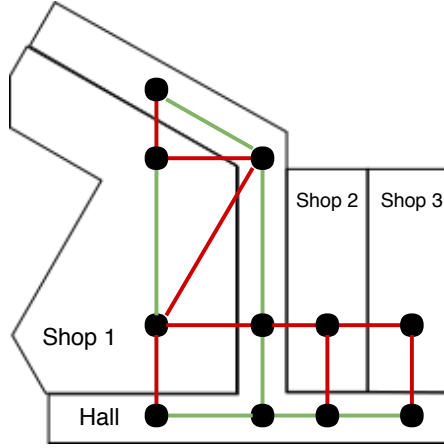


Fig. B.3: The demo-zone in Kolding Storcenter, consisting of three shops. Black dots denote thermal zones. The hallway area has been discretized into several thermal zones, to model thermal interaction across hallways. The different edge colors exemplify different thermal resistances between thermal zones.

2.4.3 Model instantiation

Generation of a model instance for the demo-zone in Kolding Storcenter consists of constructing the graph-representation of the thermal zones, as overlaid in **Figure B.3** – and selecting suitable parameters for the dynamical model. A parameter set consists of thermal capacitances, thermal resistances and parameters specific to the fan coils (valves, coils). These can be obtained to a large extent through air flow measurements, shop dimensions and table-lookup – this process and the resulting parameters are described in [10]. Selected parameters are given in **Table B.1**. The large internal heat gains, \dot{Q}_{int} , are dominated by display lighting; characteristic to shopping centers. The state, input and output vectors are given as:

$$\mathbf{x} = [\mathbf{T}_{\text{shop}}, \mathbf{T}_{\text{supply}}, \mathbf{T}_{\text{hall}}, T_{\text{fwd,cold}}, \mathbf{x}_{\text{aux}}]^T \quad (\text{B.15})$$

$$\mathbf{u} = [\mathbf{T}_{\text{supply,r}}, T_{\text{fwd,cold,r}}]^T \quad (\text{B.16})$$

$$\mathbf{y} = [\dot{Q}_{\text{cool}}, \text{COP}, P_{\text{cool}}]^T \quad (\text{B.17})$$

where \mathbf{x}_{aux} denotes auxiliary states in connection to local temperature controllers.

Note that this particular model instance of Kolding Storcenter only considers cooling, given that parameters have been identified using measurements obtained under summer-like conditions. Also specific to this model instance is the added power consumption aspects, given in Eq. (B.10). For

this paper $\eta_{\text{cool}} = 0.6$ has been selected, to model the efficiency from Central Cooling Unit (CCU) to cooling capacity available at the shops. Also, a COP model is introduced, to model a dependency on ambient temperature and forward temperature:

$$\text{COP}(\Delta T) = 6.66 - 0.36 \text{ K}^{-1} \Delta T + 0.007 \text{ K}^{-2} \Delta T^2 \quad (\text{B.18})$$

$$\Delta T = T_{\text{amb}} - T_{\text{fwd,cold}} \quad (\text{B.19})$$

This particular COP model is based on data from the CCU product catalog and COP relationship with temperature difference as described in [13]. Power measurements are needed to obtain a more realistic model.

Table B.1: Selected model parameters

Shop	Area [m ²]	C_{zone} [kJ/K]	C_{act} [kJ/K]	\dot{Q}_{int} [kW]
Shop 1 (1)	500	3×10^3	0.75×10^3	13.0
Shop 1 (2)	500	3×10^3	0.75×10^3	13.5
Shop 2	250	1.5×10^3	0.375×10^3	5.75
Shop 3	250	1.5×10^3	0.375×10^3	6.75

2.4.4 MPC

We formulate the case-specific MPC as follows:

$$\min_{\mathbf{T}_{\text{supply},r}, T_{\text{fwd,cold},r}} J = \sum_{k=n}^{n+H} \|\mathbf{x}(k)\|_2 + \|u(k)\|_2 \quad (\text{B.20})$$

subject to:

$$\mathbf{x}(k+1) = \mathbf{A} \mathbf{x}(k) + \mathbf{B} u(k) \quad (\text{dynamics})$$

$$\mathbf{y}(k) = \mathbf{C} \mathbf{x}(k) + \mathbf{D} u(k) \quad (\text{output})$$

state constraints:

$$20^\circ\text{C} \leq \mathbf{T}_{\text{shop}}(k) \leq 25^\circ\text{C}$$

$$10^\circ\text{C} \leq \mathbf{T}_{\text{supply}}(k) \leq 20^\circ\text{C}$$

input constraints:

$$10^\circ\text{C} \leq \mathbf{T}_{\text{supply},r}(k) \leq 20^\circ\text{C}$$

$$5^\circ\text{C} \leq T_{\text{fwd,cold},r}(k) \leq 25^\circ\text{C}$$

output constraints:

$$P(k) = P_{\text{ref}}(k-n) \quad \text{for} \quad n_{\text{on}} \leq k+n \leq n_{\text{off}} \quad (\text{B.21})$$

We choose a cost function, which is quadratic in the states and inputs, to minimize deviations from the operating point in which our model is linearized;

thereby minimizing discrepancies between our nonlinear and linear model. Other options could include terms to either also minimize power consumption or maximize COP, but this is not within the scope of this paper.

Sample time for MPC has been chosen as 5 min and the prediction horizon has been chosen as 5 h; giving $H = 60$. The nonlinear model of the temperature dynamics for the Kolding Storcenter demo-zone has been linearized around an operating point corresponding to nominal values with summer weather conditions. Furthermore, the linear model has been discretized with the MPC sample time of 5 min.

2.5 Case Study Simulations

Simulations of the proposed direct control solution for load-shifting has been conducted, simulating 5 h, during opening hours of shops in Kolding Storcenter. Given the relatively short time-frame, ambient temperature is assumed constant.

The nonlinear model is used for simulations, holding the control inputs constant for each MPC sample. Simulations have been done using Python and SciPy[14], employing CVXPY[15] for MPC.

For a first simulation, the following continuous-time power constraint is employed:

$$P_{\text{cool}}(t) = 12.5 \text{ kW} \quad \text{for} \quad 12 \text{ h} \leq t \leq 13 \text{ h} \quad (\text{B.22})$$

Given a nominal power consumption, P_{nominal} of $\approx 19.5 \text{ kW}$, the intended behavior is that load is shifted to before this interval, by pre-cooling the shops. This will allow the shop temperatures to drift towards their upper limit within the interval of restricted power consumption. This is exactly what happens, as can be seen from the simulation response in **Figure B.4a**.

As seen, the use of forward temperature reference as control input, means that a higher COP is achieved during the interval of low power consumption. This in principle allows for larger power curtailments, as more cooling capacity is obtainable from the same power input. This does, however, also mean that there is room left for energy efficiency improvements during nominal operations.

Some drawbacks are apparent. First, the power consumption constraint is violated, by using more power than given in the constraints; approximately 1 kW more. This is due to the discrepancy between the linear model employed in MPC and the nonlinear model used for simulations. Second, the load-shifting induces a large spike in power consumption, just before the period of low power consumption. This spike is not desirable, given exactly the reasons why load-shifting is investigated – to avoid strain on the power grid.

For a second simulation, the following continuous-time energy constraint is employed:

$$\int_{12\text{h}}^{13\text{h}} P_{\text{cool}}(t) - P_{\text{nominal}} \, dt = -7 \text{ kWh} \quad (\text{B.23})$$

where $P_{\text{nominal}}(t)$ is the nominal power consumption. The intent of this constraint is to shift the consumption of 7 kWh energy.

To pose this constraint, we augment our model with a new state, E :

$$\Delta \dot{E} = P_{\text{cool}}(t) - P_{\text{nominal}} \quad (\text{B.24})$$

The constraint can then be formulated as:

$$\Delta E(13\text{h}) - \Delta E(12\text{h}) = -7 \text{ kWh} \quad (\text{B.25})$$

The simulation results with this constraint is given in **Figure B.4b**. The most notable take-away, comparing the use of a power constraint to the use of an energy constraint, is that using the energy constraint introduces integral-action to the MPC that eliminates the discrepancy in energy consumption between linear and nonlinear model – and so the constraint is not violated when simulating with the nonlinear model.

In the simulations, it is possible to shift a load of approximately 7 kW for 1 h, without violating specified comfort constraints, as the shop temperatures are kept above 21 °C and below 24.5 °C. Knowing that the CCU responsible for supplying demo-zone is rated with a cooling capacity of 186 kW and that the total cooling capacity for Kolding Storcenter as 3500 kW, the results can be extrapolated as:

$$P_{\text{curtail},1\text{h},\text{total}} = 7 \text{ kW} \frac{3500 \text{ kW}}{186 \text{ kW}} = 131 \text{ kW} \quad (\text{B.26})$$

Considering that the example simulations do not exploit the entire comfort band, the potential power curtailment for Kolding Storcenter is thus on the order of 100 kW for 1 h, using the approach outlined in this paper.

2.6 Conclusions

This paper has introduced a general control scheme for providing energy flexibility in the form of general load-shifting, by considering time-dependent constraints on either power consumption or energy consumption in MPC. The control scheme applies to buildings with centralized climate control and is applicable to a Danish shopping center, as demonstrated in the presented case-study.

2.6. Conclusions

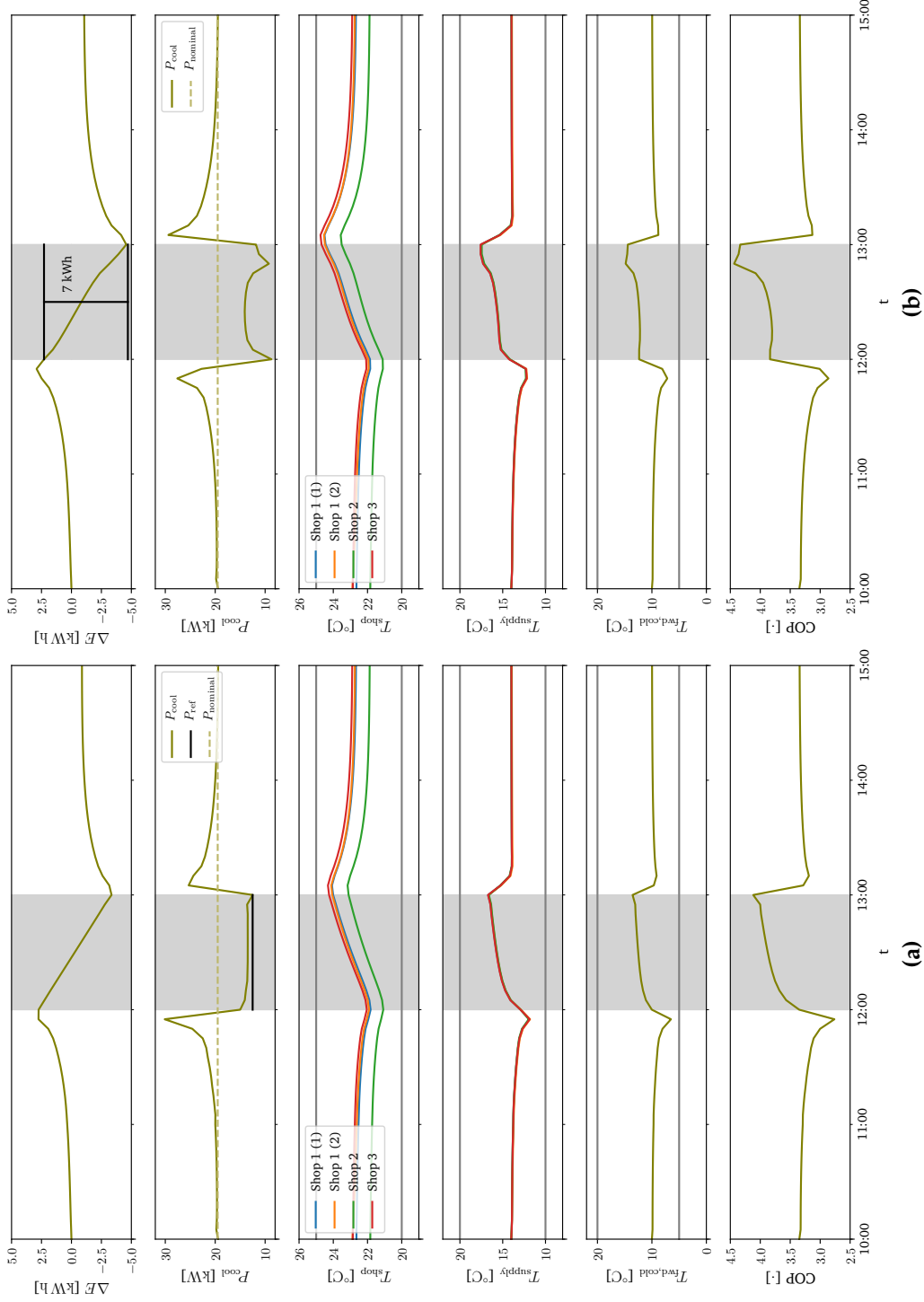


Fig. B.4: MPC simulations providing load-shifting through direct control of power consumption. Two different constraints are used, to enforce load-shifting – a constraint on power consumption (a) and a constraint on energy consumption (b). Shaded-area shows interval where load is to be reduced and grey lines indicate min/max. values. Both constraints provide load-shifting, as the MPC cools down shops in due time, to let shop temperatures drift and thereby exploit the temperature comfort band for reduced power/energy consumption. The system return to nominal conditions, when the time-dependent constraints are no longer active. Using a power consumption constraint suffers from the discrepancy between linear and nonlinear model, giving a steady-state error, given the offset to power reference. This is eliminated by using an energy constraint, due to integral action.

The scheme considers direct control of power/energy consumption, through a reference signal. Employing a constraint on power consumption suffered steady-state errors, given discrepancies between the linear prediction model and nonlinear simulation model. Several methods are available to deal with such steady-state errors – but a possibility is also to employ nonlinear models for prediction. The steady-state errors were however avoided using constraints on energy consumption.

The approach shows a significant potential power curtailment on the order of 100 kW, for the shopping center considered, for a period of 1 h. A more thorough flexibility characterization is however needed to further verify these results – also, models for power consumption require measurements to be verified. This is scheduled as future work in the present project, where also a practical demonstration is planned.

Acknowledgement

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Paper C

Nonlinear Model Predictive Control for Energy Efficient Cooling in Shopping Center HVAC

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The layout has been revised.

Abstract

In this paper we present a novel approach to control a shopping center HVAC system which significantly reduces the amount of energy spent on cooling. The HVAC system considered is for a section of a Danish shopping center, including central ventilation, fan coil units and a chiller delivering cooling.

The system is modeled using a grey-box RC-equivalent approach and identified parameters using measurement data extracted directly from the Building Management System from several days of live operation. From a comparison with measurements it has been concluded that the model is usable for the purpose of control design.

An optimal control problem to minimize total cooling effort by manipulating central ventilation supply temperature and chiller forward temperature has been posed. The intention being to shift cooling from the chiller to the ventilation unit when cooling is available through a low ambient temperature – avoiding both heating and cooling the same air. This optimal control problem has been used as the basis for a Model Predictive Controller. For prediction purposes, input signals from the previous days have been used, exploiting the fairly periodic behaviour of the system.

Simulation studies show that during heating seasons the Model Predictive Controller is capable of shifting the entire cooling load to the ventilation unit and still maintain the same performance as the nominal controller. This amounts to energy savings of 21 %.

3.1 Introduction

Buildings are responsible for one third of the total energy consumption in Denmark [1]. Energy refurbishments of older buildings typically consider the building envelope itself which can be an expensive and cumbersome task. Instead, replacing or updating the heating and or cooling equipment can with less effort amount to larger energy savings [2] and can prove to be a more attractive investment in energy renovations from an owner's/operator's point of view.[3, 4]

One approach to reductions in energy consumption for buildings is through control applications. This has been extensively studied with the majority of recent work within predictive control [5, 2]. With many buildings featuring multi-zone characteristics and with the inherent scale of some commercial systems, both distributed [4], decentralized [3] and hierarchical [6] solutions have previously been investigated. Considering implementation costs, a centralized solution may still be more attractive for the owners/operators, which is a necessity for wider adoption and hence energy savings on a larger scale. In [7], a novel central Nonlinear Model Predictive Control (NMPC) is designed and implemented for a Constant Air Volume (CAV) Heating Ventilation and Air Conditioning (HVAC) system with large energy savings.

This paper presents work that is part of a project named Smart Energy Shopping Centers (SEBUT)[8]. SEBUT aims at developing control systems, knowledge services and tools for energy refurbishments of shopping centers in Denmark. SEBUT takes a holistic approach to both energy efficiency and flexibility [9]; touching upon indoor air quality, advanced control of indoor climate and lighting, energy storage, user requirements, behavior and potential barriers.[8]

The work presented in this paper is a continuation of the work done in [10], in which we presented a control-oriented multi-zone model suitable for modeling the temperature dynamics in a shopping center; the model was then used in a preliminary control design to increase energy efficiency of a chiller supplying shop-level cooling. In this paper we focus on the same system but extend it to include the central ventilation unit – this adds to the complexity of producing the required cooling capacity as efficiently as possible, given that both the ventilation unit and chiller can produce and deliver cooling. This complexity is not handled in the current control configuration, which amounts to energy wasted through a lack of coordination between production and consumption. We consider how we can manage the complexity through a control design that seeks to efficiently meet the shop-level cooling demands.

In **Section 3.2**, the shopping center and HVAC system in question is accounted for, together with issues in the current control solution. Following, in **Section 3.3**, the model equations are introduced together with parameterization. **Section 3.4** describes the control design with simulation results presented in **Section 3.5**. Conclusions are given in **Section 3.6**.

Notation-wise, matrices are denoted in uppercase bold, e.g. **A**, vectors are denoted in lowercase bold, e.g. **x**. Dependence of variables on time t , $\mathbf{x}(t)$, is implied and will not necessarily be written explicitly.

3.2 System overview

In this paper we consider a typical HVAC layout exemplified by *Kolding Storcenter*, a mall in Denmark. The shops in Kolding Storcenter are ventilated using a CAV scheme, featuring fan coil units that enables heating and cooling at shop-level; allowing for local control of the supply temperature to each shop. Each shop is, depending on size, outfitted with several fan coil units – they are however controlled as a single unit. The shops are divided into clusters, where each cluster is supplied with ventilated air from a Central Ventilation Unit (CVU) and chilled water for shop-level cooling from a Central Cooling Unit (CCU). For heating, hot water from District Heating (DH) is supplied to all fan coils. This general HVAC layout is depicted in **Figure C.2**. In Kolding Storcenter, a demo-area has been established for the

3.2. System overview

SEBUT project. The demo-area consists of three shops supplied by the same CVU and the same CCU.

Each fan coil has two heat exchangers, one for cold and one for hot water, to which the flow is controllable with motor-controlled valves. Each shop features a temperature controller; manipulating valve openings to control shop supply temperature (T_{supply}) – the shop-local control is depicted in **Figure C.1**. Reference signals for shop-local control are given by the Building Management System (BMS); in which the central HVAC control is implemented.

The CCU, a heat pump, is controlled independently of the cooling requirements of the shops; the forward temperature ($T_{\text{fwd,cool}}$) is typically kept constant around 10 °C.

The CVU delivers ventilated air at a controlled supply temperature (T_{vent}) and an almost constant flow (\dot{m}_{vent}). There is no recirculation in the CVU; air is drawn in at ambient temperature (T_{amb}) and then either cooled or heated (using its own heat pump, not the CCU), depending on the setpoint for the supply temperature. The setpoint for supply temperature is determined by a controller acting on extract temperature from the shops.

One issue with the current control architecture lies in the lack of coordination between the shop-local temperature control, the control of the CVU and the CCU. This lack of coordination shows as cases where energy is spent on e.g. heating air up in the CVU and then more energy is spent on cooling it down again in some of the fan coils. This specific issue is depicted in **Figure C.3**.

In order to obtain measurements and manipulate with the HVAC system we ‘piggyback’ on the central control by interfacing with the existing BMS network through the use of a *gateway unit* [11]. This provides us with the same measurements and ways of actuation as the BMS. The gateway unit features an Internet connection, allowing new control algorithms to run on a device/platform that is not physically in the mall in question; e.g. in a cloud-environment.

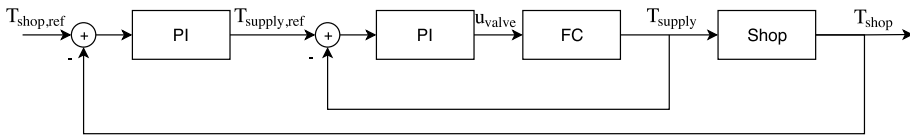


Fig. C.1: The shop-local temperature control is implemented as two PI regulators in a cascade configuration. The FC block is a fan coil unit.

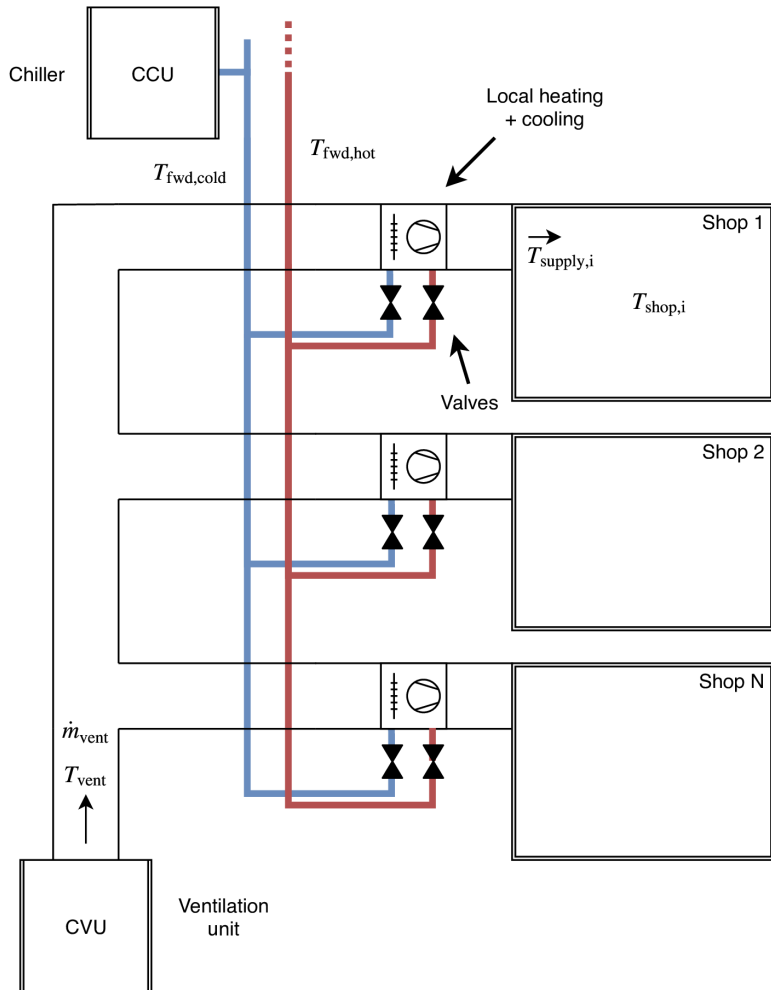


Fig. C.2: The HVAC layout of Kolding Storcenter; depicting a cluster of shops supplied by shared central ventilation; CVU. A central chiller, CCU, supplies chilled water to each fan coil, for local cooling. Heating is through DH. No return pipes/ducts are depicted.

3.2. System overview

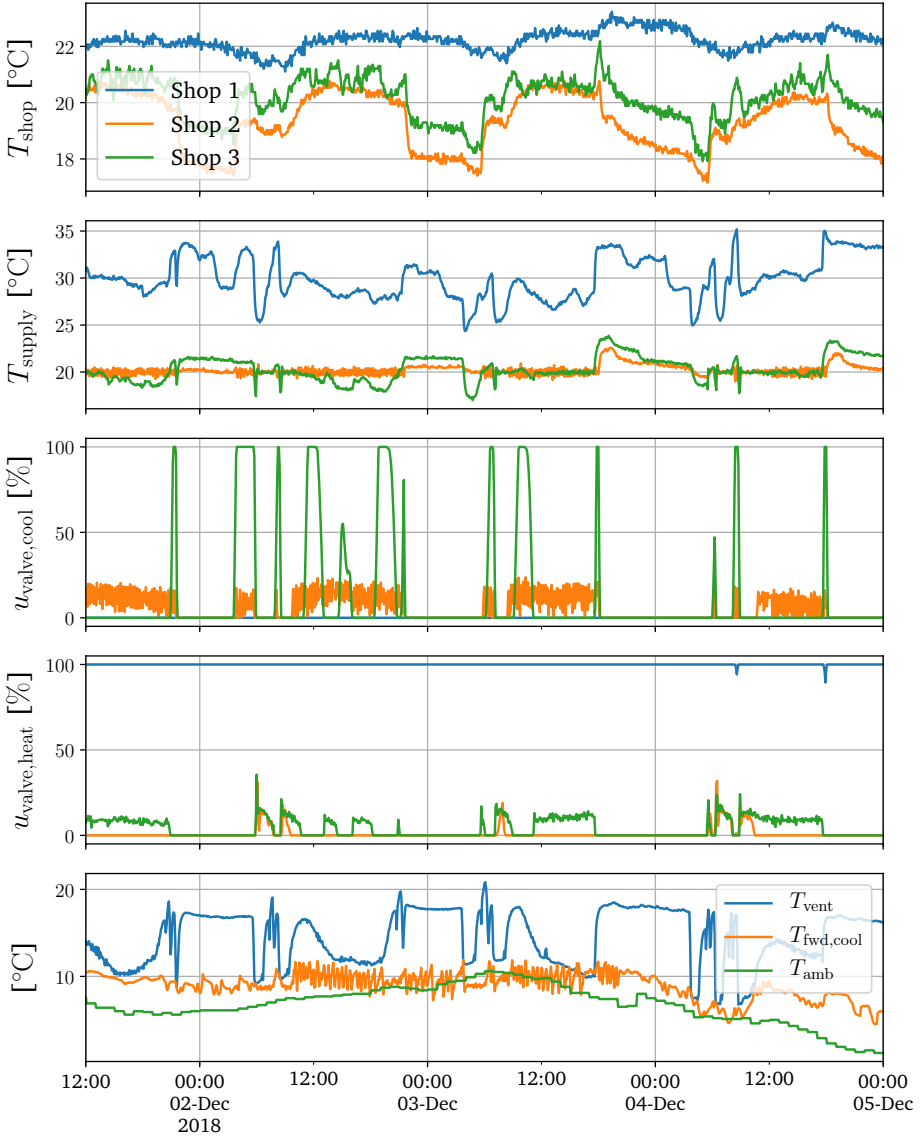


Fig. C.3: Measurement data extracted from the BMS. The three shops in the demo-area behave differently; Shop 1 features large heating demand (heating valve saturating at 100 % all the time). Shop 2 and Shop 3 utilize both cooling and heating. $T_{\text{vent}} > T_{\text{amb}}$ at certain times through operational hours due to heating in the CVU.

3.3 Model

The model presented in this section builds upon the work in [10], where we employ a grey-box RC-equivalent modeling paradigm, treating each shop as a thermal zone with a lumped thermal capacitance.

3.3.1 Temperature dynamics

With N being the number of shops considered, the temperature dynamics of the i -th shop is given by:

$$C_{\text{shop},i} \dot{T}_{\text{shop},i} = \dot{Q}_{\text{FC},i} + \dot{Q}_{\text{center},i} + \dot{Q}_{\text{int},i} \quad (\text{C.1})$$

where $C_{\text{shop},i}$ is the lumped thermal capacitance of shop i , $T_{\text{shop},i}$ is the shop temperature and $\dot{Q}_{\text{center},i}$ is the heat flow to/from the surroundings. $\dot{Q}_{\text{FC},i}$ is the heat flow supplied by fan coils and $\dot{Q}_{\text{int},i}$ models the internal heat gain, e.g. heat gain from occupancy, lighting and appliances. No heat exchange between the shops is considered as $\dot{Q}_{\text{int},i}$ dominates the energy balance, given the amount of display lighting. Also, no heat gain from solar load is included, as the shops are not exposed to direct sunlight.

The supply temperature dynamics for the i -th shop is given by:

$$C_{\text{supply},i} \dot{T}_{\text{supply},i} = \dot{Q}_{\text{vent},i} + \dot{Q}_{\text{recirc},i} + \quad (\text{C.2})$$

$$\dot{Q}_{\text{cool},i} + \dot{Q}_{\text{heat},i} - \dot{Q}_{\text{FC},i} \quad (\text{C.3})$$

where $C_{\text{supply},i}$ is the lumped thermal capacitance for the fan coils and $T_{\text{supply},i}$ is the temperature of the supply air to the shop. $\dot{Q}_{\text{cool},i}$ is heat flow from central cooling, $\dot{Q}_{\text{heat},i}$ is heat flow from heating and $\dot{Q}_{\text{vent},i}$ is heat flow from central ventilation. Also, for the fan coils, some air is recirculated from the shops giving the heat flow $\dot{Q}_{\text{recirc},i}$.

Collected as matrix/vector expressions, we consider the temperature dynamics in the following form:

$$\mathbf{C}_{\text{shop}} \dot{\mathbf{T}}_{\text{shop}} = \dot{\mathbf{Q}}_{\text{FC}} + \dot{\mathbf{Q}}_{\text{center}} + \dot{\mathbf{Q}}_{\text{int}} \quad (\text{C.4})$$

$$\mathbf{C}_{\text{supply}} \dot{\mathbf{T}}_{\text{supply}} = \dot{\mathbf{Q}}_{\text{vent}} + \dot{\mathbf{Q}}_{\text{recirc}} + \dot{\mathbf{Q}}_{\text{cool}} + \dot{\mathbf{Q}}_{\text{heat}} - \dot{\mathbf{Q}}_{\text{FC}} \quad (\text{C.5})$$

with all vectors belonging to \mathbb{R}^N and the \mathbf{C} -matrices being square and invertible.

3.3.2 Heat flows

The heat flow supplied by the fan coils is given by:

$$\dot{Q}_{\text{FC}} = \dot{\mathbf{M}}_{\text{FC}} c_{p,\text{air}} (\mathbf{T}_{\text{supply}} - \mathbf{T}_{\text{shop}}) \quad (\text{C.6})$$

3.3. Model

where $\dot{\mathbf{M}}_{\text{FC}} \in \mathbb{R}^{N \times N}$ is a diagonal matrix with $\dot{m}_{\text{FC},i}$ – the air flow to the i -th shop – in the diagonal. The specific heat capacity is denoted $c_{p,\text{air}}$.

Each fan coil supplies air at a rate of μ kg/s constantly during operation (CAV), where β is from ventilation and $(1 - \beta)$ is recirculated. Scaling with number of fan coils in a given shop:

$$\dot{\mathbf{M}}_{\text{FC}} = \mu \mathbf{N}_{\text{FC}} \text{ kg/s} \quad (\text{C.7})$$

where $\mathbf{N}_{\text{FC}} \in \mathbb{R}^{N \times N}$ is a diagonal matrix with number of fan coils, $N_{\text{FC},i}$, in the diagonal.

Heat flows from CVU and recirculation are given as:

$$\dot{\mathbf{Q}}_{\text{vent}} = \beta \dot{\mathbf{M}}_{\text{FC}} c_{p,\text{air}} (T_{\text{vent}} \mathbf{1} - \mathbf{T}_{\text{supply}}) \quad (\text{C.8})$$

$$\dot{\mathbf{Q}}_{\text{recirc}} = (1 - \beta) \dot{\mathbf{M}}_{\text{FC}} c_{p,\text{air}} (\mathbf{T}_{\text{shop}} - \mathbf{T}_{\text{supply}}) \quad (\text{C.9})$$

where $\mathbf{1}$ is a vector of all ones.

The heating/cooling heat flows are given as:

$$\dot{\mathbf{Q}}_{\text{cool}} = \alpha \mathbf{u}_{\text{valve,cool}} c_{p,\text{water}} (T_{\text{fwd,cool}} \mathbf{1} - \mathbf{T}_{\text{supply}}) \quad (\text{C.10})$$

$$\dot{\mathbf{Q}}_{\text{heat}} = \alpha \mathbf{u}_{\text{valve,heat}} c_{p,\text{water}} (T_{\text{fwd,heat}} \mathbf{1} - \mathbf{T}_{\text{supply}}) \quad (\text{C.11})$$

where α is a combined term for coil efficiency and valve characteristics; it is assumed constant. The valve openings, $\mathbf{u}_{\text{valve}}$, are determined by the governing PI regulators also included in the model.

The CVU is controlled through a setpoint for T_{vent} . This control is modelled with some first order dynamics – equivalently for the CCU:

$$\tau_{\text{CVU}} \dot{T}_{\text{vent}} = T_{\text{vent,r}} - T_{\text{vent}} \quad (\text{C.12})$$

$$\tau_{\text{CCU}} \dot{T}_{\text{fwd,cool}} = T_{\text{fwd,cool,r}} - T_{\text{fwd,cool}} \quad (\text{C.13})$$

The total combined cooling capacity of the CVU and the CCU, $\dot{Q}_{\text{cool,tot}}$, is modelled as:

$$\dot{Q}_{\text{cool,CCU}} = \sum_1^N \dot{Q}_{\text{cool},i} \quad (\text{C.14})$$

$$\dot{Q}_{\text{vent,cap}} = \beta \sum_1^N \dot{m}_{\text{FC},i} c_{p,\text{air}} (T_{\text{vent}} - T_{\text{amb}}) \quad (\text{C.15})$$

$$\dot{Q}_{\text{cool,tot}} = \dot{Q}_{\text{cool,CCU}} + \dot{Q}_{\text{vent,cap}}^- \quad (\text{C.16})$$

where $\dot{Q}_{\text{vent,cap}}^-$ is the negative part of $\dot{Q}_{\text{vent,cap}}$, thus only taking cooling into account.

3.3.3 Parameterization

Model parameters have been identified using a combination of manual air flow measurements, measurements taken from the BMS and shop dimensions. Steady-state data has been used to determine magnitudes of heat flows and shop dimensions have been used to determine thermal capacitances. Internal heat gains are assumed constant throughout shop opening hours; this assumption is to a large extent valid given that display lighting dominates the term.

Parameters used are given in **Table C.1** and **Figure C.4** compares model simulation with measurements obtained from the BMS in order to validate the use of the model for control purposes.

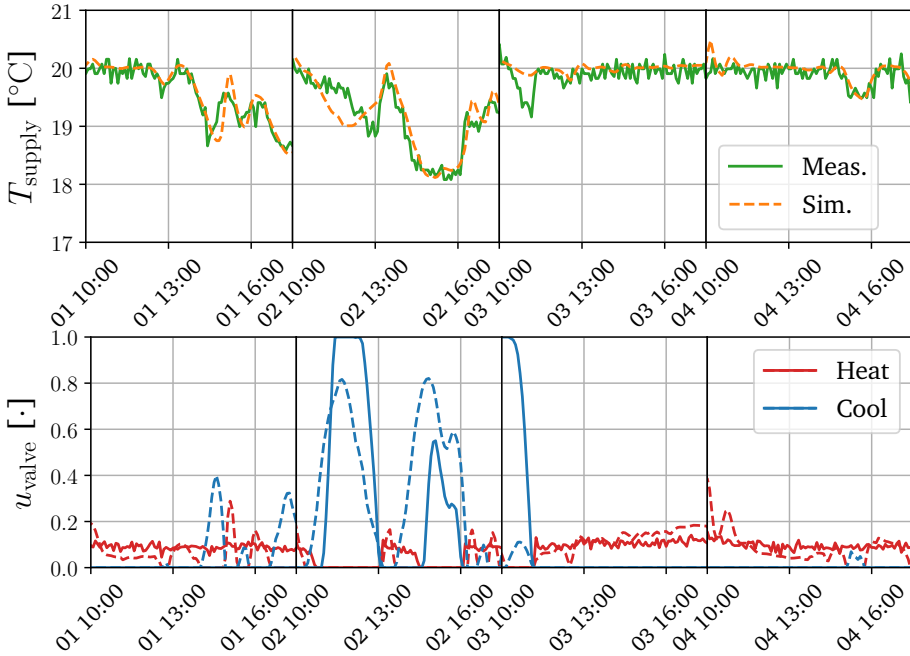


Fig. C.4: Comparing simulated response (dashed) with measured (solid) for a single shop during hours where the HVAC was running. The fit is not perfect, but deemed good enough for the basis of a control design. Most notable shortcomings stem from the stochastic nature of \dot{Q}_{int} .

3.4. Minimizing energy spent on cooling through control

Table C.1: Selected model parameters

Shop	Area [m ²]	C_{shop} [kJ/K]	C_{supply} [kJ/K]	\dot{Q}_{int} [kW]
Shop 1	650	7.0×10^3	2.3×10^3	8.0
Shop 2	250	2.7×10^3	0.9×10^3	4.8
Shop 3	250	2.7×10^3	0.9×10^3	3.2
$\alpha = 0.05 \text{ kg/s}, \quad \mu = 0.36 \text{ kg/s}, \quad \beta = 1/3$ $T_{\text{fwd,heat}} = 55^\circ\text{C}, \quad \tau_{\text{CVU}} = 15 \text{ min}, \quad \tau_{\text{CCU}} = 5 \text{ min}$				

3.4 Minimizing energy spent on cooling through control

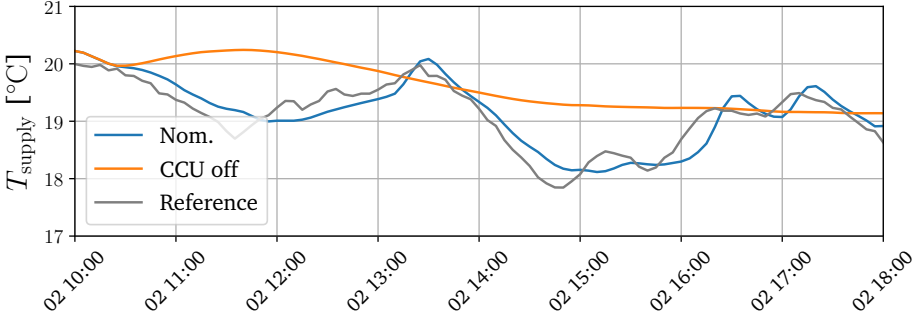


Fig. C.5: Simulation where the CCU is turned off (*CCU off*) compared with a simulation with nominal/historical inputs, showing the supply temperature response for *Shop 3*. Turning the CCU off introduces a loss in regulation power for the shop-local supply temperature control, visible as a degradation in tracking performance.

As described in **Section 3.2**, there are two ways of heating the air and two ways of cooling it; either centrally at the CVU or locally at the fan coils. One issue is the apparent use of the CCU for cooling, even during the heating season. The issue is rooted in the control configuration lacking coordination – but just as much in the large internal heat gains in the shops. One attempt at minimizing energy spent on cooling, would be to simply turn off the CCU during heating season. However, given the current control architecture, this can pose problems with lack of regulation power for the control of shop-local supply temperature. This is exemplified with a simulation where the CCU is turned off. The supply temperature for *Shop 2* is for this simulation depicted in **Figure C.5**.

3.4.1 Optimal Control Problem

In order to avoid the loss of regulation power by turning off the CCU, we consider Model Predictive Control (MPC) to shift the cooling capacity from the CCU to the CVU instead. This seems sensible, especially during the heating season, as the ambient temperature is typically lower than the desired supply temperature – giving a free source of cooling.

We consider $T_{\text{vent},r}$ and $T_{\text{fwd,cool},r}$ as our control inputs – and use historical input data for the exogenous inputs, including references for shop-local supply temperature control. No observer is necessary since measurements are available for all states. The state, control input, exogenous input and output is given as:

$$\mathbf{x} = [\mathbf{T}_{\text{shop}}^T, \mathbf{T}_{\text{supply}}^T, T_{\text{vent}}, T_{\text{fwd,cold}}, \mathbf{x}_{\text{aux}}^T]^T \quad (\text{C.17})$$

$$\mathbf{u} = [T_{\text{vent},r}, T_{\text{fwd,cool},r}]^T \quad (\text{C.18})$$

$$\mathbf{u}_{\text{ex}} = [\mathbf{T}_{\text{supply},r}^T, T_{\text{amb}}]^T \quad (\text{C.19})$$

$$\mathbf{y} = [\dot{Q}_{\text{cool,tot}}] \quad (\text{C.20})$$

where \mathbf{x}_{aux} denotes auxiliary states related to the supply temperature PI regulators. We then formulate our optimal control problem as:

$$\min_{\mathbf{u}} J = \int_{t_0}^{t_f} \mathbf{y}^T \mathbf{y} dt \quad (\text{C.21})$$

subject to:

$$\dot{\mathbf{x}} = \mathbf{f}(t, \mathbf{x}(t), \mathbf{u}(t), \mathbf{u}_{\text{ex}}(t)) \quad (\text{dynamics})$$

$$\mathbf{y} = \mathbf{h}(t, \mathbf{x}(t), \mathbf{u}(t), \mathbf{u}_{\text{ex}}(t)) \quad (\text{output})$$

and subject to state and input constraints:

$$\begin{aligned} \mathbf{T}_{\text{shop,min}} &\leq \mathbf{T}_{\text{shop}} \leq \mathbf{T}_{\text{shop,max}} \\ \mathbf{T}_{\text{supply,min}} &\leq \mathbf{T}_{\text{supply}} \leq \mathbf{T}_{\text{supply,max}} \\ T_{\text{vent},r,min} &\leq T_{\text{vent},r} \leq T_{\text{vent},r,max} \\ T_{\text{fwd,cool},r,min} &\leq T_{\text{fwd,cool},r} \leq T_{\text{fwd,cool},r,max} \end{aligned}$$

where \leq should be taken element-wise in the vector case. This optimal control problem seeks to minimize $\|\dot{Q}_{\text{cool,tot}}\|^2$, which effectively means minimizing the total cooling effort described by Eq. (C.16). Note that the objective function does not directly penalize the control signal. Usually this would let MPC exhibit a ‘bang-bang’ behavior. In our case, however, the output contains a (practically) static contribution from the control signal via the expression for total cooling effort, as can be seen in Eq. (C.15). This prevents

adverse control behavior consistent with the simulation response presented in **Section 3.5**. It should also be noted, that constraints on the relationship between state and input are to be considered, e.g. $T_{\text{fwd,cool,r}} < T_{\text{supply,i}}$ when cooling – however, simulation results without (see **Section 3.5**) give feasible solutions.

3.5 Simulation studies

We have used *CasADi*[12] through Python to model the nonlinear system dynamics and to pose, discretize and solve the optimal control problem using a multiple-shooting approach.

We let the prediction horizon be equal to $t_{\text{predict}} = 5 \text{ h}$ and the sampling time of both measurements and our MPC is fixed to 5 min. Given that we do not know the exogenous inputs 5 h in advance, we utilize the fact that the system is fairly periodic and employ inputs from the previous day (delayed 24 h) for prediction purposes.

The state and inputs constraints have been set to:

$$\begin{aligned} 17^\circ\text{C} &\leq T_{\text{shop,i}} && \leq 25^\circ\text{C} \\ 10^\circ\text{C} &\leq T_{\text{supply,i}} && \leq 35^\circ\text{C} \\ 5^\circ\text{C} &\leq T_{\text{vent,r}} && \leq 25^\circ\text{C} \\ 5^\circ\text{C} &\leq T_{\text{fwd,cool,r}} && \leq 25^\circ\text{C} \end{aligned}$$

We have conducted simulation experiments of 4 consecutive days in December 2018. Given the operational hours of the HVAC system in Kolding Storcenter, the simulation has been limited to the hours between 08:00 and 18:00 during these days, for a total simulation time of 40 h. The results are shown in **Figure C.6**.

The results show noticeable less degradation of regulation power for the shop-local supply temperature control (for *Shop 2*), as compared to **Figure C.5** where the CCU was simply turned off. This is to a large extent achieved by letting the CVU run with a supply temperature closer to the ambient temperature, hereby delivering more base cooling to the fan coils. This lowers the need to actuate the valves for cooling from the CCU. Also, $T_{\text{fwd,cool}}$ is set significantly higher than for nominal control, which decreases cooling when exercising the cooling valves. From both input signals, it is possible to see the correlation with the previous day's cooling load by comparing with the shown T_{supply} .

Looking at the response for $\dot{Q}_{\text{cool,CCU}}$ it is very clear that the reduction in cooling supplied by the CCU when using MPC is equivalent to simply turning off the CCU – as desired. This does not necessarily mean that net

energy spent is lower, however, as it could simply be that energy spent on heating is equally higher.

Therefore we investigate the sum of heat flows responsible for both active heating and active cooling in the fan coils:

$$\dot{Q}_{\text{tot,cap}} = \dot{Q}_{\text{vent,cap}} + \dot{Q}_{\text{cool,CCU}} + \sum_1^N \dot{Q}_{\text{heat},i} \quad (\text{C.22})$$

From **Figure C.6** it is shown that $\dot{Q}_{\text{tot,cap}}$ is generally lower when using the designed MPC than when using the nominal control; we calculate the difference in energy consumption:

$$\begin{aligned} E_{\text{saved}} &= \int_0^{40\text{h}} \dot{Q}_{\text{tot,cap,nom}} - \dot{Q}_{\text{tot,cap,MPC}} dt \\ &\approx 230 \text{ kWh} \end{aligned} \quad (\text{C.23})$$

which is equivalent to a 21 % decrease.

3.6 Conclusions

This paper has through simulation studies demonstrated a control design which effectively minimizes energy spent on cooling during heating season, in the HVAC system of a Danish shopping center. A problem that stems from the control configuration which lacks coordination between supply and consumption of heating and cooling. By minimizing the energy spent on cooling in the heating season, it was found that energy savings of approximately 21 % are achievable. The design and simulations were carried out for a small section of the mall, but given the decentralized HVAC architecture described, it should be scalable to the entire mall.

From the simulation studies it can also be concluded, that it is probably not necessary to use MPC to achieve the same effect. To a large extent, the savings can be achieved by simply turning off the chiller and letting the ventilation unit run with a supply temperature closer to the ambient temperature. This can be achieved with a much simpler and less involved implementation, than for the case of MPC; hereby moving the solution from simple via complex to lucid[13] and avoiding stability and robustness considerations for a complex solution. This does not undermine the applications of MPC, but in this case MPC is used in an exploratory approach to first discover the desired behavior of a more simple solution.

As such, these results form the basis of a control design which will be implemented and tested through the SEBUT project.

3.6. Conclusions

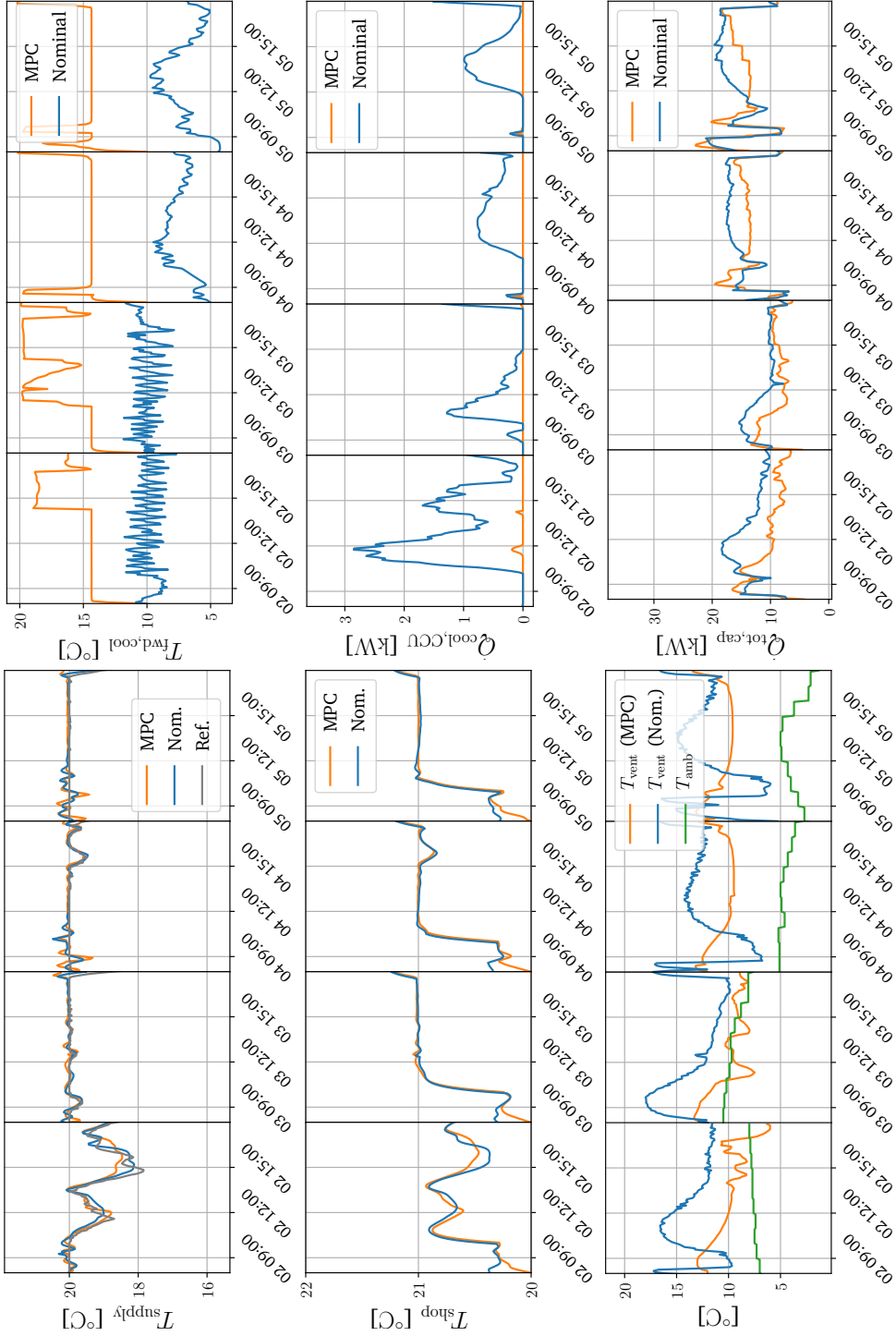


Fig. C.6: Comparison of MPC and nominal control through simulation of 4 days. Simulation has been limited to between 8:00 and 18:00 due to operational hours of the HVAC. Simulations are based on data extracted from the BMS. The MPC attempts to lower energy spent on cooling by running with a lower T_{vent} .

Acknowledgement

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References

Paper D

Low-Complexity Hierarchical Control for Distributed Shopping Center HVAC

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Andrew G. Alleyne, Jakob Stoustrup

The paper has been published in the
1st Virtual IFAC World Congress, 2020.

The layout has been revised.

Abstract

In this paper we present a low-complexity hierarchical control approach to fan-coil-based HVAC systems, applicable to shopping centers as exemplified through a case study of a Danish shopping center. Although Model Predictive Control remains the optimal approach performance-wise, we show that we can recover 66% of the performance with the proposed approach, when considering no model-mismatch for the Model Predictive Controller. The recovered performance comes with the added benefits of increased reusability and operator transparency, given no dependence on an accurate dynamical model and lower complexity.

4.1 Introduction

Buildings constitute one third of the energy consumption in Denmark ([1]) and while energy refurbishments of older buildings often consider the building envelop itself, there is a large potential for energy savings through updating Heating Ventilation and Air Conditioning (HVAC) equipment which – given an assumed lesser effort – can prove a better investment for building owners/operators. One way of going about this is through control applications.

Energy savings within building control have been studied extensively, with the majority of work revolving around Model Predictive Control (MPC) ([2, 3]) and with buildings exhibiting multi-zone characteristics, both distributed ([4]) and decentralized ([5]) predictive control have been investigated.

In [6] a setpoint-manipulating MPC for minimizing energy consumption, in a fan-coil-based shopping center HVAC system (see **Figure D.1**), was designed and evaluated through simulations. It was compared to a simulation with historical input data, in which setpoints were set manually by building operators. The general issue with manually setting setpoints is that in a large scale system, it can be difficult for operators to balance production and demand of cooling, leading to situations such as cooling air in fan coils, where energy has already been spent heating it in an Air Handling Unit (AHU). In [6], the MPC introduced the necessary coordination, but it was concluded that the problem could be solved using a simpler control method; i.e. with less complexity. The desire to consider less complexity is not rooted in computational issues, especially when considering building systems with large time constants, rather, the reasoning lies in control reusability and operator transparency. Control reusability is key, considering impact on energy savings when one control approach can be deployed among multiple buildings. However, using MPC requires an accurate system model, which severely diminishes the reusability and induces a high initial investment, as also demon-



Fig. D.1: From left; AHU, chiller unit and Building Management System (BMS) gateway for remote data acquisition and control, situated at Kolding Storcenter, a Danish shopping center.

strated in [7]. This, together with availability of both data and processing power has sparked a significant interest in data-based and learning-based methods; both considering learning the model, as highlighted in the references treated in [8] and learning the control itself, e.g. using reinforcement learning ([9]). This does not, however, cater to the issue of operator transparency.

This work investigates the use of hierarchical control. In [10] and [11], which deal with experimental validation of hierarchical control for thermal management, it is concluded that hierarchical control is especially suitable in complex thermal management systems, where a decentralized approach can result in poor performance, due to the general difficulty of managing couplings between subsystems.

We propose a low-complexity hierarchical control architecture to coordinate production and demand in a fan-coil-based HVAC system – avoiding heavy-use of a model in an effort to provide reusability and operator transparency. To the knowledge of the authors, this type of architecture does not appear in the academic literature.

In **Section 4.2** we present the class of HVAC systems considered, the proposed hierarchical control framework, and MPC as a reference approach. Following that, in **Section 4.3**, we present a Danish shopping center as a case study and in **Section 4.4** we present simulation studies, comparing the proposed hierarchical control to MPC. Conclusions are given in **Section 4.5**.

Notation-wise, vectors are denoted in lowercase bold, e.g. \mathbf{x} . Time-dependence of variables, $\mathbf{x}(t)$, is implied and will not necessarily be written explicitly. Derivative with respect to time is written as $\dot{\mathbf{x}}$.

4.2 Methods

4.2.1 Shopping Center HVAC

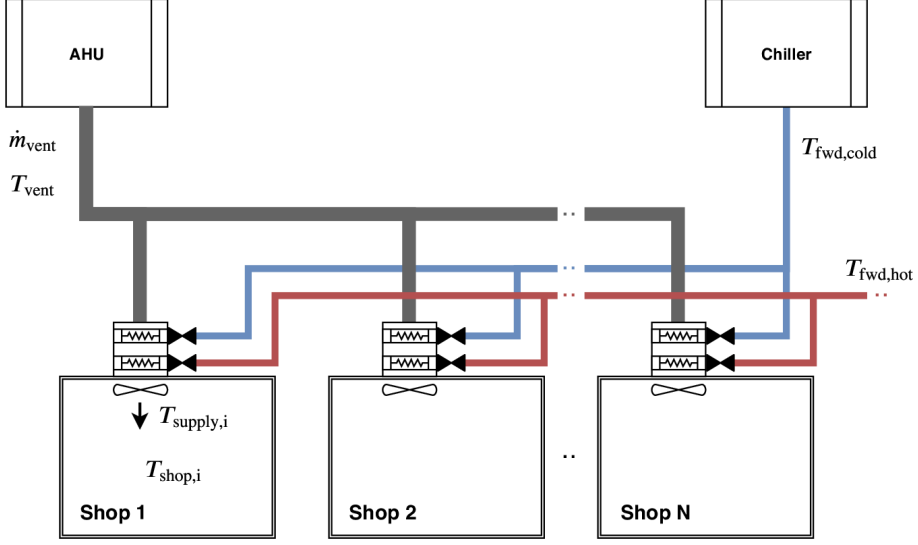


Fig. D.2: Fan-coil-based shopping center HVAC layout. No return ducts/pipes are depicted to simplify the diagram.

In this paper we focus on shopping centers that employ fan coils for shop temperature control. The general HVAC system considered is depicted in **Figure D.2**. The system consists of:

- AHU supplying ventilated air with flow \dot{m}_{vent} and at temperature T_{vent} .
- Chiller supplying chilled water at temperature $T_{fwd,cold}$ for cooling coils in fan coils.
- N shops with fan coils.

Hot water to heating coils in fan coils is supplied at temperature $T_{fwd,hot}$ by, e.g., district heating. Shop temperature, $T_{shop,i}$, for the i -th shop can be regulated by manipulating shop supply temperature, $T_{supply,i}$. This is done through heating and cooling valves in the fan coils. We consider a Constant Air Volume (CAV) setup for the fan coils; they are either ON or OFF.

We assume a decentralized control configuration, where each shop has its own temperature controller, manipulating valve openings to reach desired shop temperature, $T_{shop,r,i}$. The AHU is controlled through operator-given setpoints, $T_{vent,r}$ and $\dot{m}_{vent,r}$, and the chiller through the setpoint $T_{fwd,cold,r}$.

4.2.2 System dynamics

We present the main dynamics considered for the system described in **Section 4.2.1**. The model is based on the previous work done in both [12] and [6] where we employ a grey-box RC-equivalent modeling paradigm, treating each shop as a thermal zone with a lumped thermal capacitance.

Temperature dynamics

Letting N denote the number of shops, the shop temperature dynamics of the i -th shop is given by:

$$C_{\text{shop},i} \dot{T}_{\text{shop},i} = \dot{Q}_{\text{FC},i} + \dot{Q}_{\text{center},i} + \dot{Q}_{\text{int},i} \quad (\text{D.1})$$

where $C_{\text{shop},i}$ is the lumped thermal capacitance of shop i , $\dot{Q}_{\text{center},i}$ is the heat flow to/from the surroundings, $\dot{Q}_{\text{FC},i}$ is the fan-coil-supplied heat flow and $\dot{Q}_{\text{int},i}$ models internal heat gain, e.g. from occupancy, lighting and appliances.

The supply temperature dynamics are modeled as:

$$C_{\text{supply},i} \dot{T}_{\text{supply},i} = \dot{Q}_{\text{AHU},i} + \dot{Q}_{\text{cool},i} + \dot{Q}_{\text{heat},i} + \dot{Q}_{\text{recirc},i} - \dot{Q}_{\text{FC},i} \quad (\text{D.2})$$

where $C_{\text{supply},i}$ is a lumped thermal capacitance for the fan coils. $\dot{Q}_{\text{AHU},i}$ is the heat flow supplied by the AHU, $\dot{Q}_{\text{cool},i}$ is the heat flow supplied by the chiller and $\dot{Q}_{\text{heat},i}$ is heat flow from heating. Some air is recirculated in the fan coils, modeled by the heat flow $\dot{Q}_{\text{recirc},i}$.

Heat flows

The heat flow supplied by fan coils to shops is given by:

$$\dot{Q}_{\text{FC},i} = \dot{m}_{\text{FC},i} c_{p,\text{air}} (T_{\text{supply},i} - T_{\text{shop},i}) \quad (\text{D.3})$$

where $\dot{m}_{\text{FC},i}$ is flow of air and c_p is specific heat capacity. Heat exchange with the surroundings, $\dot{Q}_{\text{center},i}$, is given as:

$$\dot{Q}_{\text{center},i} = UA_{\text{center}} (T_{\text{center}} - T_{\text{shop},i}) \quad (\text{D.4})$$

where UA is a heat transfer coefficient and T_{center} is a lumped shopping center temperature, modelling the temperature in the shopping center as a whole:

$$\begin{aligned} \dot{T}_{\text{center}} = & \tau_{\text{extract}} (T_{\text{extract}} - T_{\text{center}}) \\ & + \tau_{\text{amb}} (T_{\text{amb}} - T_{\text{center}}) \end{aligned} \quad (\text{D.5})$$

4.2. Methods

where τ is a time-constant, T_{extract} is temperature of air extracted from shops by the AHU (return air) and T_{amb} is ambient temperature (outside). The heat flow supplied by the AHU to the fan-coils is modeled as:

$$\dot{Q}_{\text{AHU},i} = \dot{m}_{\text{FC},i} c_{p,\text{air}} (T_{\text{vent}} - T_{\text{supply},i}) \quad (\text{D.6})$$

$$\dot{Q}_{\text{AHU}} = \sum_i^N \dot{Q}_{\text{AHU},i} \quad (\text{D.7})$$

For heating and cooling, the heat flows are modeled as:

$$\dot{Q}_{\text{cool},i} = \alpha_{\text{cool}} u_{\text{valve,cool},i} c_{p,w} (T_{\text{fwd,cold}} - T_{\text{supply},i}) \quad (\text{D.8})$$

$$\dot{Q}_{\text{heat},i} = \alpha_{\text{heat}} u_{\text{valve,heat},i} c_{p,w} (T_{\text{fwd,hot}} - T_{\text{supply},i}) \quad (\text{D.9})$$

$$\dot{Q}_{\text{chiller}} = \sum_i^N \dot{Q}_{\text{cool},i} \quad (\text{D.10})$$

where α is a constant modeling both coil efficiency and valve characteristics and $u_{\text{valve},i}$ is valve opening degree. Given the assumption that each shop has its own temperature controller, the valve openings are controlled by PI regulators included in the model. $\dot{Q}_{\text{recirc},i}$ is modeled as a heat exchange with extract air:

$$\dot{Q}_{\text{recirc},i} = UA_{\text{FC}} (T_{\text{extract}} - T_{\text{supply},i}) \quad (\text{D.11})$$

Finally, first order dynamics govern the control of both AHU and chiller:

$$\dot{T}_{\text{vent}} = \tau_{\text{AHU}} (T_{\text{vent},r} - T_{\text{vent}}) \quad (\text{D.12})$$

$$\dot{T}_{\text{fwd,cold}} = \tau_{\text{chiller}} (T_{\text{fwd,cold},r} - T_{\text{fwd,cold}}) \quad (\text{D.13})$$

4.2.3 Hierarchical control framework

To introduce the necessary coordination we consider a hierarchical control framework, depicted in **Figure D.3**.

Where:

- \dot{Q}_{AHU} is the heat flow from AHU to the shops¹.
- \dot{Q}_{chiller} is the heat flow from chiller to the shops.
- $\mathbf{u}_{\text{AHU}} \in \mathbb{R}^{n_{\text{u,AHU}}}$ is control input affecting \dot{Q}_{AHU} .
- $\mathbf{u}_{\text{chiller}} \in \mathbb{R}^{n_{\text{u,chiller}}}$ is control input affecting \dot{Q}_{chiller} .

¹Or more specifically, the fan coils.

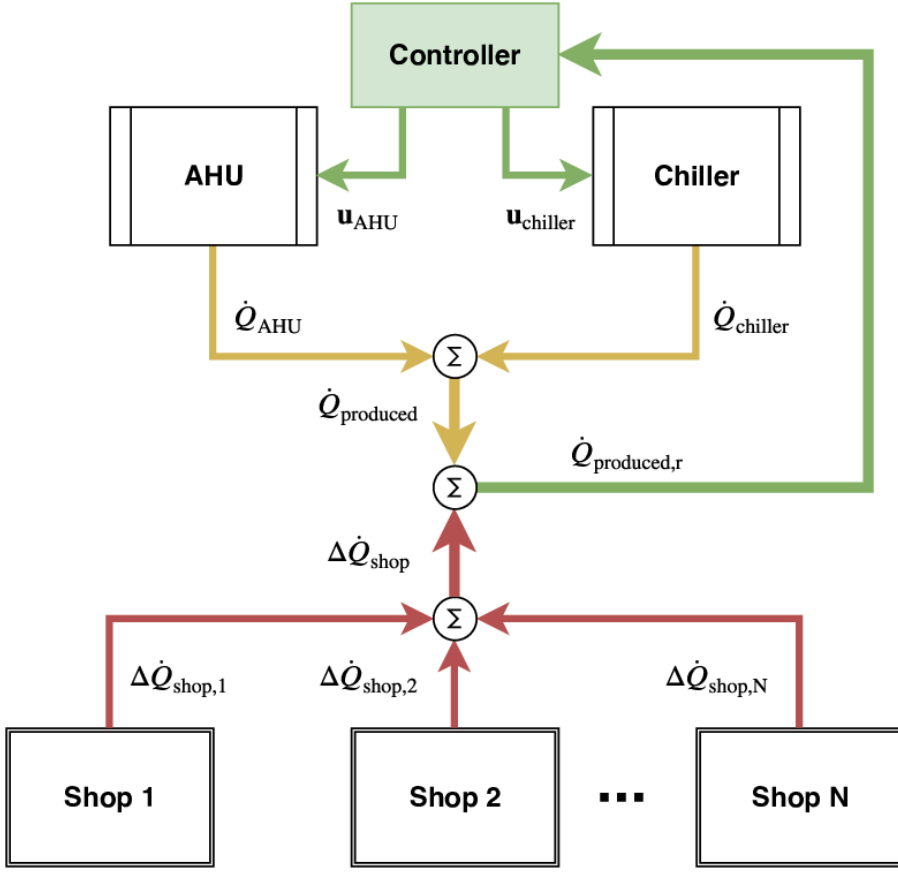


Fig. D.3: Hierarchical control framework; separating *production* (AHU, chiller) from *demand* (shops).

and where:

$$\dot{Q}_{produced} = \dot{Q}_{AHU} + \dot{Q}_{chiller} \quad (D.14)$$

$$\dot{Q}_{demand} = \dot{Q}_{produced} + \Delta \dot{Q}_{shop} \quad (D.15)$$

Here, $\dot{Q}_{demand} = \sum_i^N \dot{Q}_{demand,i}$, denotes the total demand for all the shops considered. When $\dot{Q}_{produced} = \dot{Q}_{demand}$, the system is balanced and the shops have enough heating/cooling capacity to meet the heating/cooling demand. In case $\dot{Q}_{produced} \neq \dot{Q}_{demand}$, then there is a discrepancy, given as:

$$\Delta \dot{Q}_{shop} = \sum_i^N \Delta \dot{Q}_{shop,i} = \dot{Q}_{demand} - \dot{Q}_{produced} \quad (D.16)$$

Note that $\Delta\dot{Q}_{\text{shop}}$ can be both positive and negative; positive in case of a heating demand and negative in the case of a cooling demand.

We can now formulate our primary control objective as minimizing $\Delta\dot{Q}_{\text{shop}}$, or equivalently as:

$$\dot{Q}_{\text{produced},r} = \dot{Q}_{\text{produced}} + \Delta\dot{Q}_{\text{shop}} \quad (\text{D.17})$$

$$\dot{Q}_{\text{produced}} \rightarrow \dot{Q}_{\text{produced},r} \text{ for } t \rightarrow \infty \quad (\text{D.18})$$

Assuming we have perfect tracking of $\dot{Q}_{\text{produced},r}$:

$$\dot{Q}_{\text{produced},r}(t) = \int_{t_0}^t \Delta\dot{Q}_{\text{shop}}(t) dt + \dot{Q}_{\text{produced}}(t_0) \quad (\text{D.19})$$

Revealing, that this approach is in fact an integral controller – integrating the demand to form the reference production.

The primary control objective can be met in many different ways if not considering the characteristics of either AHU or chiller – and can also be met by manually operating the setpoints of the AHU and chiller, as the capacities just have to be *large enough* to not saturate the fan coil valves for longer durations. Instead, it is more interesting to introduce a secondary control objective, to also minimize the cost of $\dot{Q}_{\text{produced}}$.

4.2.4 Hierarchical Controller

We propose a controller with the objectives presented in **Section 4.2.3** that does not require a dynamical model of the system; instead we only consider static model equations for the heat flows taken into account, namely \dot{Q}_{AHU} and \dot{Q}_{chiller} , which in this case are given by Eq. (D.7) and Eq. (D.10) in **Section 4.2.2**.

For $\Delta\dot{Q}_{\text{shop}}$, we could let it be based on the heat flows considered for the shop temperature dynamics. This choice will however be very model-dependent. Instead, we propose to estimate $\Delta\dot{Q}_{\text{shop}}$ as:

$$\Delta\dot{Q}_{\text{shop}} = \dot{m}_{\text{vent,nom}} c_{p,\text{air}} \sum_i^N e_i \quad (\text{D.20})$$

where $\dot{m}_{\text{vent,nom}}$ is the nominal air flow from the AHU and e_i is the error signal for the i -th shop temperature controller. If we let C be the cost (e.g. power consumption) of supplying $\dot{Q}_{\text{produced}}$, we can formulate an optimization problem, which seeks to minimize $\Delta\dot{Q}_{\text{shop}}$ and C_{produced} :

$$\mathbf{u} = [\mathbf{u}_{\text{AHU}}, \mathbf{u}_{\text{chiller}}]^T \quad (\text{D.21})$$

$$\min_{\mathbf{u}} J = q_d (\dot{Q}_{\text{produced},r} - \dot{Q}_{\text{produced}})^2 + q_c C \quad (\text{D.22})$$

subject to:

$$\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max}$$

where $\dot{Q}_{\text{produced}}$ is given as a function of \mathbf{u} , q_d and q_c are tuneable weights and \leq is taken element-wise.

In **Figure D.3** we only consider an AHU and a chiller. The method would however also handle any other given cooling unit or heating unit, as the production is abstracted away behind $\dot{Q}_{\text{produced},r}$, which can potentially be both positive when considering heating and negative when considering cooling. In the case of an economizer – or any passive cooling or heating unit – its contribution could be directly handled as a disturbance added to $\dot{Q}_{\text{produced}}$. Due to the proposed demand estimate being based on error signals it is however handled transparently, as we only act on deviations.

4.2.5 Reference Controller: MPC

For comparison purposes, we present a MPC with the same objectives as for the hierarchical controller in **Section 4.2.4**. This reference controller will require a dynamical model and here we use the model described in **Section 4.2.2**. We let the dynamics be given by:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{u}_{\text{ex}}, \mathbf{p}) \quad (\text{D.23})$$

where $\mathbf{x} \in \mathbb{R}^{n_x}$ is the state, $\mathbf{u} \in \mathbb{R}^{n_u}$ is controllable inputs, $\mathbf{u}_{\text{ex}} \in \mathbb{R}^{n_{u,\text{ex}}}$ is exogenous inputs and $\mathbf{p} \in \mathbb{R}^{n_p}$ are parameters. Then we pose an optimal control problem to be solved with a receding horizon:

$$\min_{\mathbf{u}} J_{\text{MPC}} = \int_{t_0}^{t_f} J \, dt \quad (\text{D.24})$$

subject to:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{u}_{\text{ex}}(t), \mathbf{p}) \quad (\text{dynamics})$$

$$\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max}$$

and subject to constraints on states as well.

4.3 Case Study: Kolding Storcenter

As a case study, we consider *Kolding Storcenter*, a Danish shopping center. Kolding Storcenter is divided up into clusters of shops; each cluster featuring a fan-coil-based HVAC layout as described in **Section 4.2.1**. A demo-area has been established for the Smart Energy Shopping Centers (SEBUT) project, consisting of one cluster of shops – and the rooftop AHU and chiller supplying the fan coils of these shops. The AHU can both heat and cool, using a built-in heat pump and direct expansion coils.

Instrumentation has been established for the demo-area using a ‘piggyback’-approach, by interfacing with the existing BMS through a *communication gateway unit*². This allows extraction of measurement data and allows for manipulation with exposed setpoints. **Table D.1** presents an overview of the, for this paper, considered inputs and outputs of the BMS, which can be manipulated and measured.

Table D.1: BMS I/O

Name	Description	Type
AHU		
T_{vent}	Supply temperature	Output
$T_{\text{vent},r}$	Supply temperature setpoint	Input
T_{extract}	Extract temperature	Output
\dot{m}_{vent}	Supply air flow	Output
$P_{\text{AHU,cool}}$	AHU power consumption (cooling only)	Output
Chiller		
$T_{\text{fwd,cold}}$	Forward temperature	Output
$T_{\text{fwd,cold},r}$	Forward temperature setpoint	Input
P_{chiller}	Chiller power consumption	Output
Shops		
$T_{\text{shop},i}$	Shop temperature	Output
$T_{\text{shop},r,i}$	Shop temperature setpoint	Output
$T_{\text{supply},i}$	Fan coil supply temperature	Output

4.3.1 Model parameterization

Parameters for the model described in **Section 4.2.2** have been identified using a combination of:

- Manual flow measurements from fan coils
- Measurements from BMS
- Shop dimensions and table-lookup

The parameters that could not be identified directly (e.g. lumped time constants) were identified by posing and solving a Least Squares Estimation problem. No heat interaction between shops is considered as internal heat gains have been found to dominate the energy balance, given the quantity of display lighting. We can therefor consider $\dot{Q}_{\text{int},i}$ constant during opening

²Neogrid Technologies. URL: <https://neogrid.dk>

hours. Note that shops are not exposed directly to sunlight and thus no heat gain from solar load is considered.

Parameters (for a single shop) are given in **Table D.2** and a comparison of shop temperature between a simulation and measurements is presented in **Figure D.4**, simulating 8 days; 4. September to 12. September – the model is deemed accurate enough for both control purposes and simulation studies.

Table D.2: Model parameters (single shop)

Area	C_{shop}	C_{supply}	\dot{Q}_{int}
250 m ²	2.0 MJ/K	1.0 MJ/K	4.0 kW
UA_{center}	UA_{FC}	α_{cool}	α_{heat}
2.0 kW/K	2.0 kW/K	0.1 kg/s	0.1 kg/s
τ_{AHU}	τ_{chiller}	τ_{extract}	τ_{amb}
1 h	1 h	1 h	6 h
$\dot{m}_{\text{vent,nom}}$		$T_{\text{fwd,hot}}$	
3.3 kg/s		55 °C	

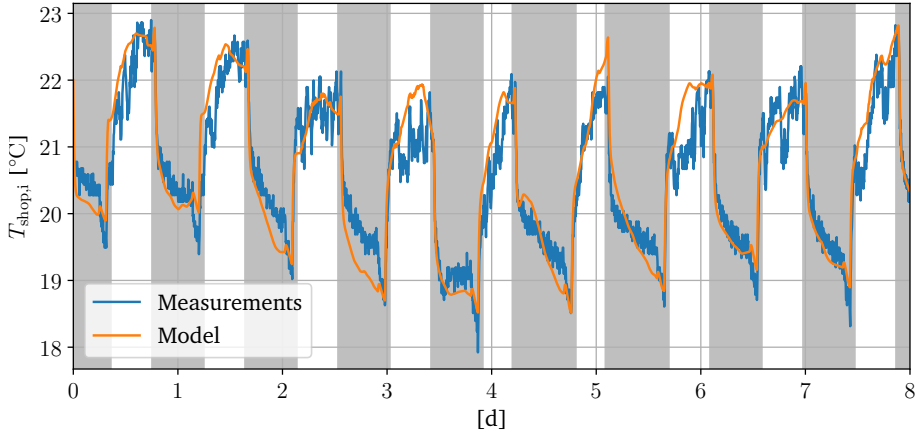


Fig. D.4: Comparing simulation of model to measurements extracted from BMS. Shop temperature for a single shop. Shaded areas indicate that the shop is closed.

4.3.2 Estimating power consumption

In order to not only balance production and demand but also meet the objective of minimizing cost, a measure for cost is needed; here we consider power

4.4. Simulation studies

consumption for both AHU and chiller.

For the chiller, we estimate power consumption as a function of $\Delta T = T_{\text{amb}} - T_{\text{fwd,cold}}$, where T_{amb} is the ambient temperature. The best fit was found by assuming the function to be a 3rd degree polynomial. The results are given in **Figure D.5**.

In the case of the AHU, we have measurements of power consumption for cooling. As such, the power consumption of the fans is *not* included and, given the ambient conditions, active heating is not present for the time period under consideration. A naïve approach would be equivalent to that of the chiller, estimating power consumption as only dependent on a $\Delta T = T_{\text{amb}} - T_{\text{vent}}$. However, recirculation and heat recovery plays a significant role for the AHU introducing a dependence on T_{extract} . Thus, for the AHU we formulate a 2nd degree polynomial dependence on both $\Delta T_{\text{amb}} = T_{\text{amb}} - T_{\text{vent}}$ and on $\Delta T_{\text{extract}} = T_{\text{extract}} - T_{\text{vent}}$, yielding:

$$\begin{aligned} \hat{P}_{\text{AHU,cool}}(\Delta T_{\text{amb}}, \Delta T_{\text{extract}}) = & \quad (D.25) \\ & a_0 \Delta T_{\text{amb}}^2 + b_0 \Delta T_{\text{amb}} + \\ & a_1 \Delta T_{\text{extract}}^2 + b_1 \Delta T_{\text{extract}} + c \end{aligned}$$

Results are given in **Figure D.5**, as both a time series comparison and a histogram of the error between measurement and estimation. There are improvements to be made in the case of the AHU, as either filtering, the inclusion of dynamics or perhaps a faster sampling time of the data will provide better results. Both fits are deemed convincing enough to be used in a control setting.

4.4 Simulation studies

Simulation studies have been conducted to evaluate the performance of the proposed hierarchical controller, compared to both a reference controller, MPC, and to a simulation with historical inputs – a nominal case. All simulations have been done using *CasADi* ([13]) through Python, where the non-linear system dynamics have been formulated. Given that measurements from the BMS are obtained with a sampling time of 5 min, this has also been chosen as sampling time for all simulations.

As a measure of cost, C , we use the power consumption estimates given in **Section 4.3.2**:

$$C = \hat{P}_{\text{tot}} = \hat{P}_{\text{AHU,cool}} + \hat{P}_{\text{chiller}} \quad (D.26)$$

and as controllable inputs we choose:

$$\mathbf{u} = [T_{\text{vent,r}}, T_{\text{fwd,cool,r}}]^T \quad (D.27)$$

We use $q_d = 2$ and $q_c = 1$ in all cases.

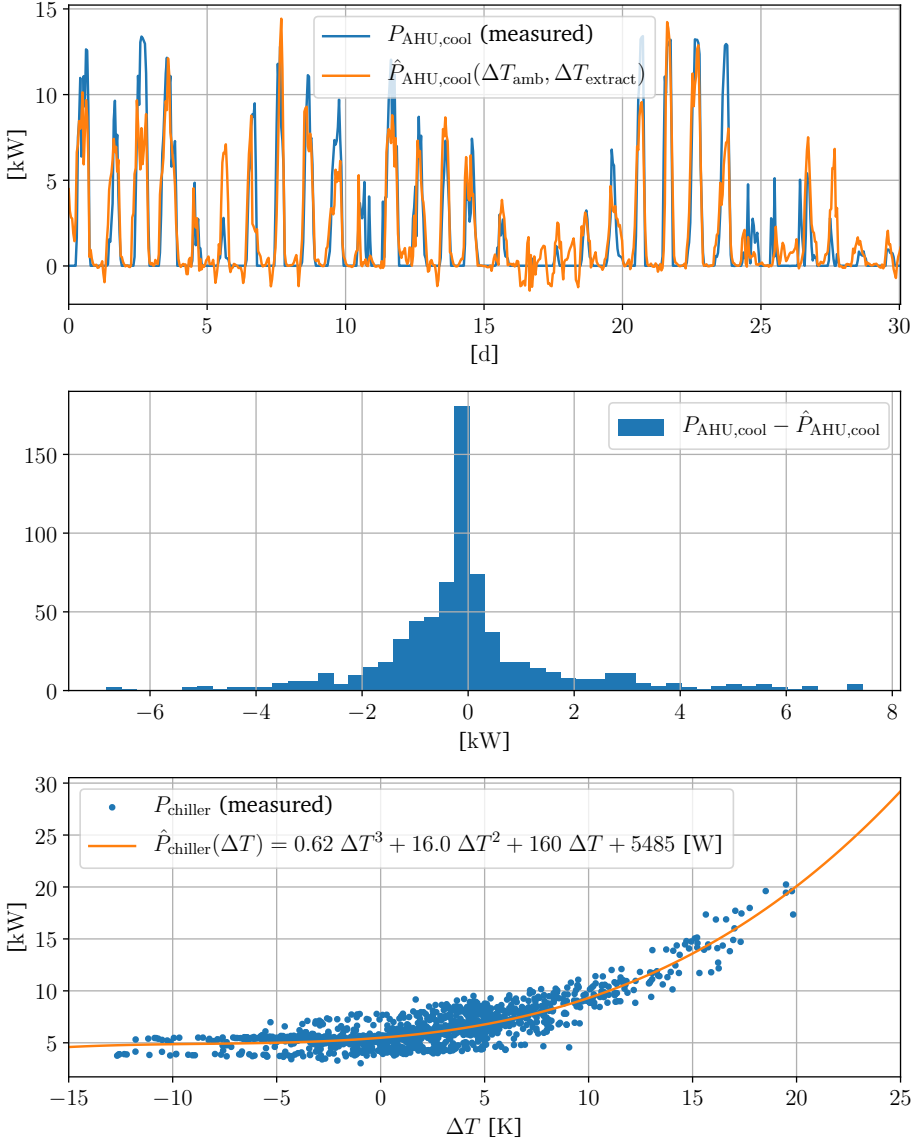


Fig. D.5: Power consumption estimation for both AHU and chiller, for demo-area in Kolding Storcenter. Coefficients for the AHU fit found as: $(a_0, b_0, a_1, b_1, c) = (131.0, 1741, -69.85, 114.0, 5750)$. Data used was from 15. August to 8. October, with T_{amb} from 2 °C to 30 °C and $T_{\text{fwd,cold}}$ from 11 °C to 14 °C.

4.4.1 Hierarchical Controller setup

We employ the hierarchical controller outlined in **Section 4.2.4** and in the expression for $\dot{Q}_{\text{produced}}$ we assume steady-state, letting $T_{\text{vent}} = T_{\text{vent},r}$ and $T_{\text{fwd,cold}} = T_{\text{fwd,cold},r}$. In calculating $\dot{Q}_{\text{produced},r}$, we consider two approaches:

Mean over last hour

Let $\Delta t = 1 \text{ h}$; then:

$$\begin{aligned} \dot{Q}_{\text{produced},r}(t) = & \\ & \frac{1}{\Delta t} \int_{t-\Delta t}^t \dot{Q}_{\text{produced}}(t) + \Delta \dot{Q}_{\text{shop}}(t) dt \end{aligned} \quad (\text{D.28})$$

We denote this version **H-1h**

Mean over next hour

Exploiting the inherent periodic behavior, with period time $T_d = 24 \text{ h}$ (see **Figure D.4**), we use yesterdays data to predict and calculate the next reference, again with $\Delta t = 1 \text{ h}$:

$$\begin{aligned} \dot{Q}_{\text{produced},r}(t) = & \\ & \frac{1}{\Delta t} \int_{t-T_d}^{t-T_d+\Delta t} \dot{Q}_{\text{produced}}(t) + \Delta \dot{Q}_{\text{shop}}(t) dt \end{aligned} \quad (\text{D.29})$$

We denote this version **H-23h**.

4.4.2 Reference Controller (MPC) setup

Using CasADi allows for also posing, discretizing and solving optimal control problems using (in this case) a multiple-shooting approach; this has been applied for the reference MPC design. The sample time is as for the simulation, 5 min and the prediction horizon chosen to be 2.5 h. Given that we do not know exogenous inputs in advance, we also here exploit the periodic behavior and use inputs from the previous day (delayed 24 h). Note that we consider \mathbf{u} as our control input.

4.4.3 Simulation setup and results

We only consider 2 shops for this simulation, with slightly different consumption profiles, given by their different shop temperature references:

$$\mathbf{T}_{\text{shop},r} = [21.5^\circ\text{C}, 22.0^\circ\text{C}]^T \quad (\text{D.30})$$

Simulating 8 days, 4. September to 12. September, using historical data we compare the four cases:

- Nominal (Purely historical inputs)
- Hierarchical Controller (H-1h)
- Hierarchical Controller (H-23h)
- MPC

Given that actuation (fan coils ON) is limited to operator set schedules, control authority is limited to these schedules; not exactly opening hours but resembling working hours of staff. The results are presented in **Figure D.6**, with shaded regions depicting when fan coils are turned OFF. Common between the three control strategies attempted, is that they all use the chiller to a lesser extent than in the nominal case, as visible in the response of $T_{\text{fwd,cold}}$. The main difference lies in the use of the AHU, where the MPC almost avoids using it, the **H-23h** uses it to some extent and the **H-1h** even more. Tracking performance is very similar, as visible from both the response of $\Delta\dot{Q}_{\text{shop}}$ and T_{shop} . The results also show, from looking at the excitation of the valve openings, how both hierarchical control and MPC end up using the heating valve to a lesser extent, as air from the AHU is delivered at a higher temperature; avoiding first spending energy cooling the air in the AHU and the heating it up again in the fan coils. Performance-wise, we compare the four cases on three metrics:

1. Root-Mean-Square Error (RMSE)

$$\bar{e} = \bar{T}_{\text{shop,r}} - \bar{T}_{\text{shop}} \quad (\text{D.31})$$

where \bar{a} denotes mean value.

2. Energy consumption

$$E_{\text{tot}} = \int_{t=0\text{d}}^{t=8\text{d}} \hat{P}_{\text{tot}} \, dt \quad (\text{D.32})$$

3. Simulation time

as a measure of complexity; this is time taken for the entire simulation to run, for each case considered. Measured on the same hardware.

Note that we only consider RMSE and energy consumption for the times when the fan coils are ON.

4.4. Simulation studies

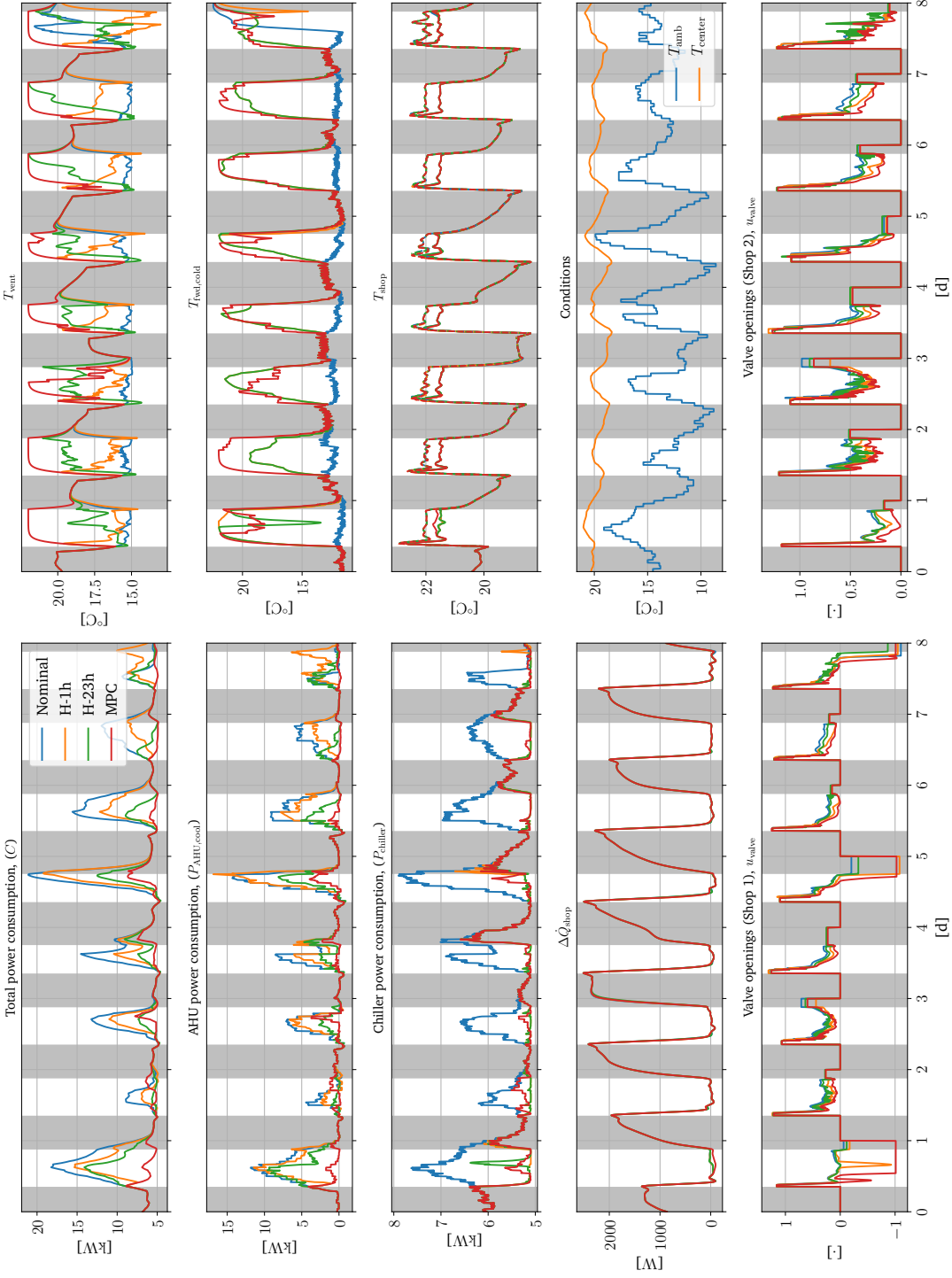


Fig. D.6: Simulation results from 8d simulation, comparison nominal case to three different control strategies. Shaded area indicates no control authority. Shop temperature, T_{shop} is depicted as a solid line for Shop 1 and a dashed line for Shop 2. Valve opening signals, u_{valve} , combines signal for both heating valve (> 0) and cooling valve (< 0).

These results are presented in **Table D.3**. Comparing RMSE values, the MPC is best and **H-23h** worst; but the difference is 0.004 K – and, as such, a fair conclusion is that the comfort performance is almost identical. Comparing energy consumption, the MPC is again best with **H-23h** second; the MPC amounting to a 44 % reduction compared to the nominal case, where **H-23h** reduces energy consumption by 29 %. As such, the MPC wins on performance. However, comparing simulation time the MPC falls short of the other methods. Here, the proposed hierarchical controllers are 17 times faster – and this is when only considering $N = 2$ shops.

Table D.3: Performance metrics

Metric	Nominal	H-1h	H-23h	MPC
RMSE	0.481 K	0.480 K	0.483 K	0.479 K
E_{tot}	918 kW h	754 kW h	649 kW h	520 kW h
t_{sim}	2 s	20 s	20 s	340 s

4.5 Conclusions

We have proposed a low-complexity hierarchical control approach to fan-coil-based HVAC systems, exemplified by the case study of a Danish shopping center. The hierarchical controller is designed to avoid the dependence on a dynamical model, while still introducing the necessary coordination for energy efficient operation, by balancing production and demand using only steady-state model information and an empirically-based model for power consumption.

Through simulation studies the proposed hierarchical controller was compared to MPC; using the same cost function but having the benefits of accurate model dynamics, as no model-mismatch is considered. Using MPC would amount to a 44 % reduction in energy consumption compared to a simulation with historical inputs (no advanced control). Using the hierarchical controller and relying only on measurements from the last hour of operation, the reduction was only 18 %; a significant reduction but not comparable to the MPC. However, exploiting the periodic behavior of the HVAC system and allowing the system to use yesterdays data to predict consumption for the next hour, the reduction was increased to 29 % – recovering 66 % of the MPC performance.

This is a promising reduction in energy consumption when considering that the hierarchical controller does not rely on model dynamics. Without the dependence on model dynamics and with the demonstrated lower com-

putational overhead, it is concluded that this low-complexity method has the potential to provide both less initial costs, less operator training overhead and thus higher reusability. This is key for energy savings, when considering the deployment among multiple buildings.

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Paper E

A Simplified Hierarchical Approach to Distributed HVAC Control - a shopping center case study

Joakim Børlum Petersen, Jan Dimon Bendtsen,
Andrew G. Alleyne, Jakob Stoustrup

The paper has been submitted for journal publication.

Paper F

Low-Complexity Hierarchical and Iterative Learning Control for Distributed HVAC

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Andrew G. Alleyne, Jakob Stoustrup

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